The Application of Statistical Process Control to Departure Reliability Improvement

THESIS

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AFIT/GOR/ENS/97M-14

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Liu Wen Chieh

Acronym List

Acronym	*Description*
ACF	Auto Correlation Function
ADT	Average Delay Time
AMC	Air Mobility Command
AMPAS	Air Mobility Performance Analysis System
AR	Autoregressive
ARL	Average Run Length
ARIMA	Autoregressive/Integratd/Moving Average
ATA	Air Transport Association
CI	Confidence Interval
CUSUM	Cumulative Sum
DOT	Department of Tranportation
DR	Departure Reliability
EWMA	Exponential Weighted Moving Average
FMC	Full Mission Capable
GDSS	Global Decision Support System
IR Chart	Individual Range Chart
LCL	Lower Control Limit
MC	Mission Capable
MFHBF	Mean Flight Hour Between Failure
MMH/FH	Maintenance Man Hour per Flight Hour
MOE	Measure of Effectiveness
MR Chart	Median and Range Chart
MRO	Mission Reliability Office
MTBUMA	Mean Time Between Unscheduled Maintenance Action

NAF .... Numbered Air Force
OAI .... Office of Airline Information
OC .... Operating Curve
OTP .... On-Time Proportion
P Chart .... Proportion Chart
PCF .... Partial Correlation Function
R Chart .... Range Chart
S Chart .... Standard Deviation Chart
S.D. .... Standard Deviation
SMP .... Service Maturity Program
SPC .... Statistical Process Control
X Chart .... Mean Chart
XR Chart .... Mean and Range Chart
XS Chart .... Mean and S.D. Chart
TACC .... Tanker Airlift Control Center
TDT .... Total Delay Time
TQM .... Total Quality Management
UK .... United Kingdom
UCL .... Upper Control Limit

Table of Contents

List of Figures

Figure		Page

Figure Page

List of Tables

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Abstract

This research effort focuses on applying statistical process control (SPC) techniques to the departure reliability improvement process for Air Mobility Command, Mission Reliability Office. Basic SPC methods, including Pareto analysis, cause and effect diagrams, and control charts are determined to be effective tools for analyzing and assessing departure reliability. In addition, two more alternative measures of effectiveness for departure reliability are evaluated and compared using AMC's data. SPC methods are also shown to be useful in assessing in performance and in dertermineing the reporting frequency for on-time performance information. Additional statistical analyses are conducted, including one-way analyses of varience, hypothesis tests, autocorrelation of time series and normal probability plots.

Keyword: Departure Reliability, SPC, Measures of Effectiveness.

The Application of Statistical Process Control to Departure Reliability Improvement

I. Introduction

1.1 General Background

Air traffic plays an ever increasing and essential role in the global economy of the modern world, impacting transportation, communication and, entertainment, etc. The reason for this is that there are no efficient alternatives to air transportation when time is a factor for personnel or cargo transport. Further, it is estimated that air traffic volume will be twice as high in the year 2000 as in 1996 ((17):13). Consequently, providing highly reliable air service becomes an important issue for developed countries.

There are, however, many causes that can reduce the advantages of air transportation. "Departure Delay" is one of these, and is probably the biggest obstacle that the air industry wants to overcome since every delay means extra operating cost, economic loss, or unsatisfied customers. Thus, reducing or preventing delays becomes a top priority in helping air transportation to stay competitive. The fact is that preventing a delay from happening is, in a way, equal to maintaining efficiency, and efficiency is the primary means of staying ahead of competition.

Many methodologies and algorithms have been developed to identify the root causes[1] of delay and to use this information to reduce or prevent them. Basically, these root causes for delays can be categorized as either noncontrollable (including causes like weather or crew rest regulations), or controllable (including causes like logistics and maintenance) ((25):18). No matter what the causes are, efforts have

[1]The most significant reasons leading the departure delays

been made to alleviate their effects.

For example, Mizumachi and Morikawa ((17):13) proposed a means of calculating the expected number of aircraft requesting take off and the expected delay time within a terminal in order to manage air traffic flow in real time. Erzberger ((8):1) enumerated "Design Principles and Algorithms" for Automated Air Traffic management, which minimize operating cost in the presence of errors in controlling aircraft to a specified landing time. Liu and Wu ((24):215) developed a new sequencing and scheduling algorithm for arrival air traffic which implements fuzzy logic in scheduling optimization model. Armstrong ((3):13) considered the scheduling problem faced by a military air transport division when required to assign a set of tasks to a limited fleet of available aircraft. Trivizas ((27):70) conducted a runway capacity study for two major airports, Frankfurt and Chicago O'Hare. Mizumachi and Ito ((13):561) developed a time domain model to control delays around a terminal area.

The preceding studies all attempted to model or minimizes the effect of controllable causes. For uncontrollable causes like weather, Smith and Orasann ((26):4563) suggested reducing delay times by changing the flight plans for aircraft. Small, Dearmon, Finnegan and Lockhart recommended ((12):895) establishing a ground delay program for an airport that has reduced arrival capacity because of weather.

Reducing delay is so important in the air line industries that most airlines set goals for on-time performance. For instance, Delta Airlines' goal is to achieve 100 percent on-time departure for the first flight of the day ((6):42). Likewise, Federal Express (FedEx) has "zero tolerance" for delay as a policy. Every working day, FedEx must anticipate the demand for their services against a consumer base that may choose to send or not to send an overnight package. They have combined aircraft scheduling and weather forecasting with a cargo prediction model in an attempt to fulfill their policy ((6):18). In general, the air transport industry continually strives to improve on-time performance in order to reduce their costs and achieve the benefits of a smoothly running air transport system.

Significant efforts have been and will continue to be made in the air industry to reduce delays. This thesis attempts to take a quality improvement approach to contribute some ideas to this field.

1.2 Problem Statement

The airline industry generally uses the proportion of on-time departures, known alternately as departure reliability (DR), as a measure of performance ((19):6). Obviously, the higher the DR, the better the performance. The Volpe National Transportation Center reports that the American air industry average on time DR is seventy-nine percent ((6):6).

The United States Air Force Air Mobility Command (AMC) also uses DR as an objective standard of performance. Its Mission Reliability Office (MRO) has particularly put focus on this issue ((6):1). AMC computes DR monthly as

$$\text{Average DR Rate} = \frac{\text{Total number of on-time departures}}{\text{Total number of departures}} \tag{1.1}$$

based on all scheduled, distinct, and separate departures on any leg of any mission ((20):1). In this computation, an on-time departure is defined as any departure that is within 15 minutes of the scheduled departure time ((1):33). All organizations under AMC, including the Tanker Airlift Control Center (TACC) and the Numbered Air Forces (NAF), use this to measure their performance.

The AMC commander currently sets an eighty-five percent average departure rate as a goal for overall command performance and is actively pursuing initiatives to measure, monitor, and improve their performance. Improvement will not come cheaply. For example, the Volpe Center estimated that, in order to increase Departure Reliability 3.0 percent, it will cost AMC approximately \$1.5 M to \$2.0 M, which does not include Air Force internal costs ((6):65). Similarly, based on Air Transport Association (ATA) data, it would cost approximately \$350,000 dollars to produce a 0.5 percent increase in on-time performance ((6):66).

In order to assist AMC in monitoring and improve DR, the general objective for this thesis is to:

> Validate AMC's process of using the Air Mobility Performance Analysis System (AMPAS) database to assess and improve departure reliability (DR) for weapon systems and accountable agencies. Where improvements can be implemented, recommend changes in how the data should be sorted, analyzed, and/or presented to AMC senior leadership (19).

In this context, the four specific and major objectives of this thesis are the following:

1. Objective 1: Verify the applicability of statistical process control (SPC) for analyzing and assessing DR. In order to do this, this thesis will:
   - attempt to determine SPC methods are the most appropriate and effective;
   - if necessary, adapt these methods for use in the dynamic environment in which AMC is actively attempting to improve DR; and
   - demonstrate their use and effectiveness.
2. Objective 2: Verify the suitability of DR in representing AMC's performance. If there are any other alternative measures of effectiveness (MOE's), identify these, demonstrate their use, and make appropriate recommendations with regard to their use.
3. Objective 3: Determine how often on-time performance information should be reported (weekly, monthly or quarterly, etc)

1.3 Preface

Since this thesis attempts to take a quality improvement approach to attack AMC's problem, the author will build up the link between the concept of quality improvement and AMC's situation and introduce the basic ideas and terms of quality improvement and SPC in Chapter Two. The author also will apply the proper

SPC techniques to identify where the greatest opportunities for improvement are, then check if any assignable cause are presented. If this does happen, look for the proper SPC techniques again to reduce or eliminate the assignable causes in order to reduce the process variation.

As far as the ideas for accomplishing specific objects, the author will evaluate the applicability for four SPC techniques. These are the cause and effect diagram, Pareto analysis, control charts, and process capability analysis. The cause and effect diagram will be shown in Chapter 2. The author will show two examples to demonstrate its use and effectiveness. Pareto analysis will be applied on the combination of different MOEs and pivots in Chapter 3; one adapted method will be shown in the late part of Chapter 3. Some further statistical analysis is conducted in the same Chapter.

The suitability and applicability of control charts will be evaluated in Chapter 4, with focus on Shewhart control charts (for detecting large shifts) and exponential weighted moving average charts (for detecting small shifts). In addition, the relationship between the DR and delay time is presented. Average run length of the control charts are also used to determine how often on-time information should be reported.

The concept of process capability will be introduced in Chapter 5. The ratios of PCR and PCR_k index are introduced. Hypothesis tests, autocorrelation tests and the normal probability plots are applied on AMC's subgroup data. Besides, Chapter 6 will summarize the work of this thesis and make specific recommendations for future work.

1.4 The AMC Database

AMC maintains DR raw material in their Global Decision Support System (GDSS). For the purpose of ease of access for all AMC users, the Tanker Airlift Control Center (TACC) designed and maintains the Air Mobility Performance Analysis

System (AMPAS) ((7)). This database contains DR information from June, 1992 to the present and was constructed using Microsoft Excel spreadsheets. Consequently, any AMC user who has Microsoft Excel can access and use this database.

This AMPAS database contains DR information relating to five different type of aircraft. Table 1.1 lists all of the types of aircraft and describes the type of missions for each.

order	Type of the Aircraft	Mission Type
1	C-5	Airlift
2	C-17	Airlift
3	C-141	Airlift
4	KC-10	Aerial Refueling / Airlift
5	KC-135	Aerial Refueling / Airlift

Table 1.1 Type of Aircraft in AMPAS

In this database, delay times are not recorded using units such as "minutes" or "hours," but rather are coded to represent the nearest tenth of an hour. Table 1.2 presents this coding, in which minutes are converted to "tenths" and each "tenth" stands for a 6-minute interval. This coding can be extended as necessary. In this thesis, the median of each interval in minutes is used as the delay time corresponding to the associated "tenth."

1.4.1 The Storage of Data. AMC stores the data in a worksheet in a list as a labeled series of rows that contain similar data. A simple example of a partial record is in Table 1.3, which only shows the first 4 columns of one single record. The first row contains column labels and the following row contains the data for a specific departure. Each row stands for a single record. Each of AMC's subordinate organizations record the departure information for each of their missions using this format. One complete record is displayed in Table 1.4. The database used in this thesis consists of 84,414 records and covers the 13-month period from June 1995 to June 1996.

order	Tenth	Minutes
1	0.0	01-02
2	0.1	03-08
3	0.2	09-14
4	0.3	15-20
5	0.4	21-26
6	0.5	27-33
7	0.6	34-39
8	0.7	40-45
9	0.8	46-51
10	0.9	52-57
11	1.0	58-63

Table 1.2 Converting Table Between Tenth and Minutes

Label	Actual Dept ICAO	Aircraft Owner	Air crew Wing	CVSMIL
Record	EGUN	043	043	KC-135

Table 1.3 Sample of Raw Data in AMPAS

Because there is much data in this list, and since it is difficult and time-consuming to obtain and read original records, AMC chose to create pivot tables in Excel to organize the source data and obtain summaries of specific statistics of interest.

1.4.2 Pivot Tables. To understand how a pivot table works, think of a list as a database, where rows are records and columns are fields. These columns are

Pivot	Actual Dept ICAO	Aircraft Owner	Aircrew Wing	CVSMIL
Info	EGUN	043	043	KC-135
Pivot	**Delay Type**	**Delay Code**	**Delay Primary time**	**Depart Year-Mt**
Info	X	106	2.5	9510/OCT
Pivot	**First Leg**	**Mission ID**	**Mission Type**	**NAF AREA**
Info	0	8mh41fp60290	REDEP	21

Table 1.4 Complete Sample of Raw Data in AMPAS

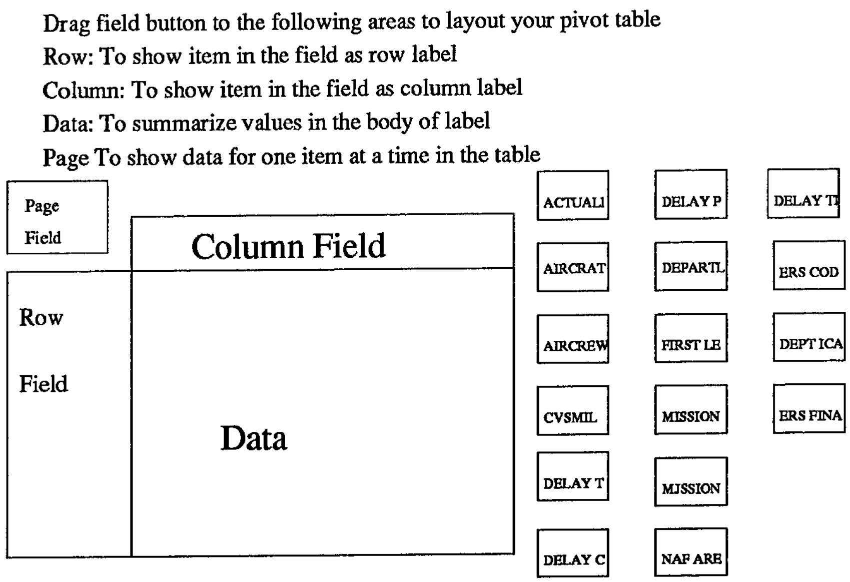


Figure 1.1 Original Pivot Table Form in Excel

also considered as pivots, and the corresponding field names can be used to organize the data. The original form of the pivot table in Excel from AMC data is shown in Figure 1.1.

Each of the 16 small rectangular boxes in Figure 1.1 corresponds to one pivot, which is the column name in the original record. There are three fields on the left that can be used to create pivot table. These are "page field," "column field" and "row field." The way to create the preferred pivot tables is to use the mouse to drag and drop the desired pivots onto one of the three fields. Then the Excel will automatically calculate the corresponding statistics associated with the pivots in all fields, and place these statistics back in the cell corresponding to the appropriate rows and columns. The nice part about pivot tables function is its flexibility. The pivots can be put in the "row field," the "column field" or the "page field" of the pivot tables. Thus, people can create a pivot table in the form they prefer in a short time. With the pivots function in Excel, all possible combinations of pivots can be tried out to explore the applicability.

By applying pivot tables, the MRO is able to use the AMPAS database to carry

out DR statistical analysis. Table 1.5 lists the pivots that have been created by AMC. Although there are many pivots that can be selected, some of these were not applied in this thesis due to the limited amount of information available. Actually, there are two considerations for the author to choose the suitable pivots. First, pivots must be completely make sense to the author. Second, some pivots have too many subgroups under them. They might be useful in the reality. However, for the sake of demonstration, they are not suitable in this context. Table 1.6 lists the pivots from the source data used by the author to create pivot tables in this thesis.

order	Pivot	Description
1	Actual Dept ICAO	The base where the aircraft actually departed
2	Aircraft Owner	The wing that owns the aircraft
3	Aircrew Wing	The wing that the aircraft is assigned to
4	CVSMIL	Type of the Aircraft
5	Delay Type	There are three different types: "C", "L" and "X"
6	Delay Codes	Delay Cause Indicator
7	Delay Primary Time	Time in Delay (tenths)
8	Delay Time	Four hours is the limit
9	Depart Year Month	Month and year of departure
10	First Leg	A one if this is the first leg of mission, null otherwise.
11	Mission Type	Self explanatory
12	NAF Area	Numbered Air Force

Table 1.5 All Pivots Form AMPAS

order	Pivot	Description
1	CVSMIL	Type of the Aircraft
2	Delay Primary Time	Time in Delay. (Minutes)
3	Depart Year Month	Month And Year of The Departure
4	Delay Code	Delay Cause Indicator
5	NAF Area	Numbered Air Force
6	Mission Type	Air Refueling and Air Lifting

Table 1.6 Pivots Used in This Thesis from AMPAS and Created by the Author

1.4.3 Workable Database Creation. After exploring the meaning of each pivot from the source data, the author tried possible combinations of pivots, and then selected the preferred pivots to create pivot tables. These tables were copied into ordinary worksheets to obtain a more useful format for subsequent analysis. Once these workable databases were created, the author transferred the results from Excel to a Unix system in order to use a software package called SAS to carry out subsequent statistical analysis.

To accomplish the statistical analysis in this thesis, the author created many different combinations of pivots. Table 1.7 summarizes four different ways that the author used to create useful information in this thesis. The second column is the name of the pivots put in the "page field," the third column lists the name of the pivot used in the "column field," and the last column shows the name of pivot used in the row field.

Case	**Page Field**	**Column field**	**Row field**
Case 1	None	Delay Codes	Delay Primary Time
Case 2	Departure Year Month	Delay Codes	Delay Primary Time
Case 3	CvsMil	Departure Year, Month	Delay Primary Time
Case 4	NAF and CvsMil	Depart Year Month	Delay Primary Time

Table 1.7 Summary of pivots used in the Workable Databases

Table 1.8 summarizes the function of each pivot table. Three possible measurement characteristics in Table 1.8 are the DR, average delay time and total delay time. Case one calculated the overall measurement characteristic for each delay code. For instance, the ADT of delay code 207 for the C-5 aircraft was 162 minutes over the 13 month period. Case 2, 3 and 4 computed the time series for each delay code or type of aircraft over the time span of this given dataset. For instance, the number of delay occurrence for delay code 207 in June 1995 was 609, 398 in July 1995, and so on.

Case	Functions
Case 1	Create the measurement characteristics for each delay code
Case 2	Create the time series of measurement characteristics for each delay code
Case 3	Create the time series of measurement characteristics for each type of aircraft
Case 4	Create the time series of measurement characteristics for each type of aircraft under NAF

Table 1.8 Summary of Functions of the Workable Databases

Case	Application
Case 1	Pareto Chart
Case 2	Pareto Chart
Case 3	Control Chart, Comparative Pareto Chart, and Process Capability
Case 4	Control Chart, Comparative Pareto Chart, and Process Capability

Table 1.9 Summary of Application of the Workable Database

Table 1.9 lists the techniques that need the corresponding database created by the associated pivot tables, Case 1 and 2 are applied in Chapter 3, and Case 3 and 4 are applied in Chapter 4 and 5.

II. Literature Review

Since this thesis attempts to take a quality improvement approach to departure reliability, the purpose of this chapter is to present the concepts definitions, and basic terminology of quality improvement and statistical process control. Additionally, in order to set the stage for the following chapters, the author will also discuss the measurement of on-time performance as presented in the current technical literature.

2.1 The Concept of Quality Improvement Process

2.1.1 The Basic Terminology of Quality Improvement. Montgomery ((18):p3) defines quality improvement as the reduction of variability in processes and products. The quality of a process can be improved by monitoring and measuring its performance over time and making necessary corrective actions to reduce the observed variability. This reduction in variability is important to an organization since, as many have written "quality is power." Further, it is well established that all organizations, including those as small as a single individual or as large as big industrial companies, a neighborhood grocery store or a sophisticated military defense program, can profit from quality improvement initiatives. Montgomery ((18):p3) states that

> There is an substantial return on the investment from an effective quality improvement program that provides increased profitability to firms that effectively employ quality as a business strategy. Effective quality improvement program can result in increased market penetration, higher productivity, and lower overall costs of manufacturing or service.

Thus, this concept of quality improvement provide a profitable approach to AMC's DR improvement process.

2.1.2 The Basic Terminology of Statistical Process Control. In any process, no matter how well designed or maintained, "natural variability" always exists

because there are many unavoidable causes for it. When the natural causes of variability are small enough to ignore and are not economically feasible to identify, detect, and eliminate, they are called "background noise," and the variability is accepted as is. The formal term for this natural variability is a "stable system of chance causes" ((18):102). When a process exhibits variation arising only from such chance causes, that process is said to be "in a state of statistical control" or simply, "in control."

There are, however, some other causes that generate variability, like operator errors, improper adjustment, and so on, that can be detected, identified and corrected. These causes are often called "assignable causes." A process with assignable causes is said to be "out of control" ((18):102).

It is natural for all organization to want to produce product or service meeting requirements, specifications, or customers' satisfaction. Statistical process control provides tools for doing so by monitoring, identifying and describing the variability that exists within processes. As Montgomery ((18):101) states

> Statistical Process Control (SPC) is a powerful collection of problem solving tools useful in achieving process stability and improving capability through the reduction of variability.

As far as the history of SPC goes, the Bell Telephone Laboratory has used statistical techniques since 1920. Statistical quality control methods were widely used at Western Electric in 1930. The American Society for Quality Control was formed in 1946 and has promoted the use of quality improvement technology for all types of products and services ever since. Japanese companies have systematically used SPC techniques for process trouble shooting, improved reliability, and improved field performance of products ((18):14). There is overwhelming evidence that those organizations that have employed SPC have gained tremendous benefits from it. All the evidence we have so far predicts that SPC could also improve AMC's situation if applied.

2.1.3 The Role of Management in Quality Improvement. Each individual plays an important role in the quality improvement process. Montgomery states

> SPC is also an attitude, a desire of all individuals in an organization for continuous improvement in quality and productivity. This attitude is best developed when management becomes involved in an on-going quality-improvement process ((18):102).

There is no doubt then that quality improvement requires a team effort. In Japan, for example, a program called quality Control (QC) circles allows for each individual to contribute. QC circle is a team of about 10 members and a supervisor who work together to improve the effectiveness of their work. This program has been extremely successful. It is estimated that 10 million workers have gone through this technique and returned an average of $5000 each ((18):102).

Management also plays a unique role in a quality improvement program. Montgomery ((18):15) states the following in defining the responsibility of management:

1. Management must do this type of statistical thinking about quality.
2. The critical role of suppliers in quality management must not be forgotten.
3. It is critical that management recognizes that quality improvement must be a total, organization-wide activity, and every organization unit must actively participate ((18):102).

Consequently, it is obvious that successful management must be a total quality management (TQM), which has the responsibility for evaluating and using information for identifying improvement opportunities in this system. The point the author wants to make is that AMC's management takes a big step toward success by evaluating the applicability of SPC. It takes great courage and responsibility to do this. However, the quality improvement process is a continuous work. There is much follow on work required.

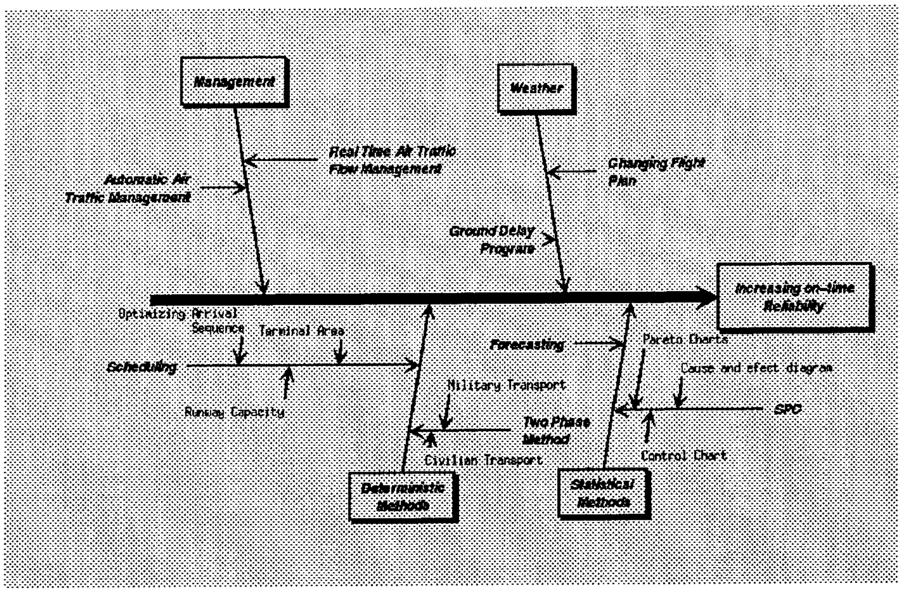


Figure 2.1 Cause-and-Effect Diagram for the Methodologies of Reducing Departure Delay

2.2 The Statistical Process Control Techniques Used in This Thesis

Statistical Process Control (SPC) is a quality improvement methodology which consists of different quality improvement and monitoring techniques. This thesis explores four SPC techniques, they are cause and effect diagram, Pareto analysis, control charts and process capability analysis. This section will develop the cause and effect diagram, the others will be introduced in the following chapters.

2.2.1 Cause-and-Effect Diagram. Cause-and-effect diagrams are used to display the relationships between factors that affect a particular quality characteristic. As an example, the author developed a cause-and-effect diagram for the methodologies for reducing departure delay discussed in Section 1.1. At first, these methodologies seemed to have their own purposes and appeared to be unrelated to each other. However, after recognizing that they all affect the main quality characteristic, departure reliability, all the methodologies could be classified into similar fields and be shown to contribute to the same quality improvement purpose. The

resulting cause-and-effect diagram is displaced as Figure 2.1.

In AMC's case, once an assignable cause has been identified, it can be isolated and a cause and effect diagram could be developed for it in order to identify the means for its potential elimination. Montgomery ((18):122) summarizes the key steps in constructing a cause and effect diagram as follows:

1. Define the problem or effect to be analyzed.
2. Form a team to perform the analysis. Often the team will uncover potential causes through brainstorming.
3. Draw the effect box and the center line.
4. Specify the major potential cause categories and join them as boxes connected to the center line.
5. Identify the possible causes and classify them into the categories developed in step 4.
6. Rank order the causes to identify those that seem most likely to impact the problem.
7. Take corrective action.

The author also picked an example from the SAS manual ((22):465) to demonstrate these key steps. Figure 2.2 shows this example. This is a case from the air industry conducted by a small group of airline division supervisors with their boss to identify the factors affecting the quality of air service. Knowing the problem is the first step, so "quality of the air service" was put in the square on the right pointed to by the main line. Since this form is created by the employee and their supervisor, this fulfilled step 2. Step 3 constructs the appearance of the cause and effect diagram. Doing step 4, the author organized the whole process into 3 main categories of service (pre-flight, in-flight, and post-flight). These are put in the squares on the branches. In step 5, all the factors associated with these three main categories are treated as a stem and connected to the branches. For instance, "prompt departure" is a factor associated with "in-flight service." It was connected to this branch with a sub-arrow.

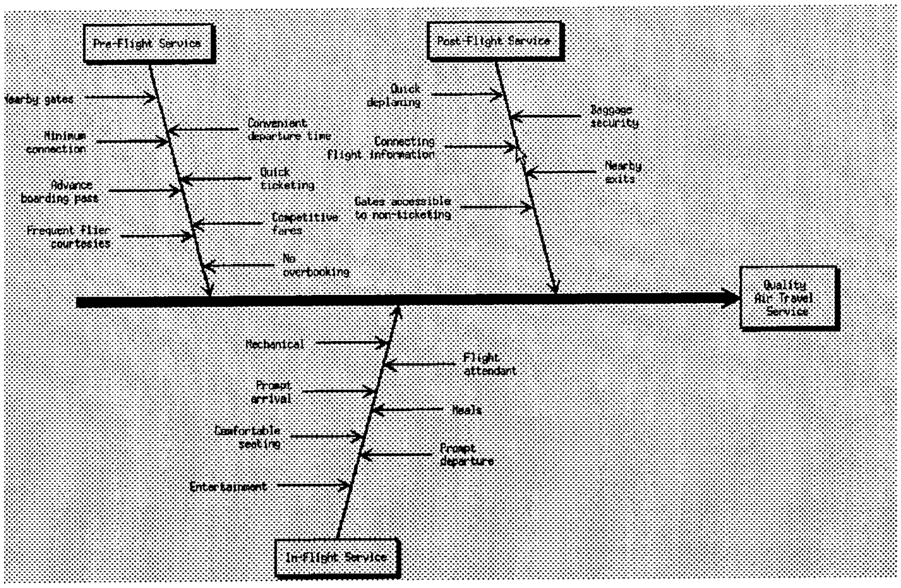


Figure 2.2 Cause-and-Effect Diagram for the Quality of Air Service

rank	Potential Causes	Possible Solution
1	Prompt departure	Boarding earlier
2	Prompt arrival	Prompt departure
3	Flight attendant	Training
4	Entertainment	Play movie
5	Meals	Offer fruits
6	Comfortable seating	Replace seating
7	Mechanical	Training

Table 2.1 Possible Solutions for the Potential Causes

Even though these is nothing under "prompt departure," it is still practical to keep on developing this subcategory if necessary. Table 2.1 demonstrates steps 6 and 7. The ranks of the potential causes are in the order of the most important to the least important. The first column of Table 2.1 shows the ranks of the potential causes and second column lists the possible solutions. The cause and effect diagram in Figure 2.1 and 2.2 are merely examples. They are presented to demonstrate their potential usefulness to AMC problem solving teams. Since this author was unable to work directly with such team, he was unable to developed a realistic AMC example.

2.3 Measures of Performance

This section provides a summary of work in the current literature relating to measurement of on-time performance in the air transport industry. There were three main reasons for this study. First, the author wanted to know if it was practical to use some other MOE instead of DR to measure on-time performance in the real world. Information from the Department of Transportation verified this is possible and suggests that "average minutes late" might be a suitable MOE. Second, the author wanted to identify applications of statistical quality improvement methods to such performance measures. A program developed for the MD-80 met this goal. Third, the author wanted to know which organizations actually monitored MOEs beyond DR to assess on-time performance. Although it was hard to find literature that directly related to overall on-time performance, information could be found associated with aircraft reliability. Since the proportion of the on-time departures can be expected to be related to aircraft maintenance problems, it seems understandable that aircraft reliability would be highly related to DR. That is, the higher an aircraft's reliability is, the higher it's DR should be. Further, if aircraft reliability can be assessed by some particular MOEs, then perhaps these same MOEs could be used to evaluate DR as well. Information from the F-15 and F-18 programs provided such details about aircraft reliability. Information from the C-17 program also backs up the idea of using DR to assess on-time performance.

2.3.1 DOT On-Time Statistics. Based upon U.S. Department of Transportation (DOT) regulations, all U.S. air carriers which earn at least one percent of the total domestic schedule-service passenger revenues need to submit on-time performance statistics to the DOT. Within DOT, airline on-time information is maintained by the Office of Airline Information (OAI) in the DOT Bureau of Transportation Statistics. Basically, OAI uses "Average Minutes Late" as a measure of effectiveness for overall on-time performance for all airlines covered by its databases. "On-Time Performance Rating" is another indicator of performance of each individual airline

that has been computed since 1987. This on-time performance rating is defined simply as the overall percentage of the reported flights arriving on time. Indeed, these on-time arrival rates have actually been promoted as inducements to attract customers.

The OAI presents the "average minutes late" statistics annually based upon monthly observations. The overall performance rating is reported quarterly and yearly.

2.3.2 MD-80 Program. In 1982, the MD-80 aircraft did not achieve the expected dispatch reliability that was expected. In this context, "dispatch delay rate" and "dispatch reliability" are defined as:

$$\text{Dispatch Delay Rate} = \frac{\text{Number of delays}}{\text{Number of departures per 1,000}} \tag{2.1}$$

$$\text{Dispatch Reliability} = 1 - \text{Dispatch Delay Rate} \tag{2.2}$$

The MD-80's manufacturer, McDonnell-Douglas, then developed a program called "Operation Go," which is referred to as a Service Maturity Program (SMP) today, in an attempt to solve possible delay-causing problems before the MD-80 officially served the worldwide market. Reducing the "dispatch delay rate" was one of the main issues considered in this program. They used this to reduce the failures that delay airplanes from departing as scheduled by identifying the "GO" items, which were simply the root causes for delays. They then tracked performance over time after making process improvements ((4):224). The MD-80 "Operation Go" SMP program achieved 99.30 percent Dispatch Reliability before this article was published.

The "GO" items here are similar to assignable causes. Pareto charts, which will be discussed Chapter 3, can identify the possible candidates for assignable causes. In the MD-80 program, the trend charts were also used to monitor the process of

tracking down and eliminating important assignable causes. This author will adapt Pareto charts to accomplish a similar objective in Chapter 3.

2.3.3 F-15 Program. The F-15 maintainability program used "Fully Mission Capable" as an indicator of aircraft performance. Based on Air Force Instruction 65-110 ((2):41), an aircraft is fully mission capable is it "is capable of doing all of its assigned mission." The ways to decides if an airplane is FMC or not is evaluated by a check list called the minimum essential equipment lists.

Three other indicators were used in this program. Mean Flight Hours Between Failure (MFHBF), Maintenance Man Hours per Flight Hour (MMH/FH) and Mean Time Between Unscheduled Maintenance Action (MTBUMA). Their history records figures are in ((11):501-502). Because a continuing maintainability emphasis had been applied to every F-15 Engineering Change Proposal (ECP), maintainability and reliability trends of the F-15 have been monitored from the beginning of this program. A linear regression model has also been fitted onto the F-15's reliability history record. The regression can be used as a technique to forecast the future tendency of the measurement characteristics.

2.3.4 F/A-18 Program. In 1976, the U.S. Navy and the McDonnell Aircraft Company (MCAIR) established a "New Look" reliability program with the F/A-18 aircraft. The main goal was to measure the F/A-18's reliability compared to the A-7E, A-6E, F-14A and F-4J/S. Three indicators used in this program are similar to those used in the F-15 program:

From the maintenance perspective, they computed "Maintenance Man Hours per Flight Hour (MMH/FH)." For the mission success requirement, they used Mean Flight Hours Between Failure (MFHBF). Full Mission Capable (FMC) was their overall MOE. In Carrier Group 14, the F/A-18 achieved 26.0 MMH/FH , 2.2 MFHBH and 80 percent FMC ((9):230).

2.3.5 C-17 Program. In 1995, the U.S. Air Force used Departure Reliability (DR) as an MOE in the C-17 war surge test program, as well as its mission capable (MC) rate which is evaluated by maintenance people like FMC. According to USAF officials, "During that test, the C-17s routinely made takeoffs with 2,500-3,000 ft. and landing within 2,000 ft. of run way. On the ground, the aircraft typically were off-loaded, refueled, loaded and prepared for takeoff within 2 hrs.15min. Besides, the C-17 takeoff gross weight was up to 460,000lb." Based on the above results, Lt Col Ron Ladnier, commander of the 17th Airlift Sqdn. at Charleston S.C. ((5):23) stated that "The results of this program has met this aircraft's performance requirements." During this test program, on-time proportion was about 96 percent, MC was over 90 percent and Mission Completion Success Probability was over 97 percent ((5):23).

2.4 Average Run Length

A minor objective of this thesis is to determine how frequently the DR information should be reported. The Average Run Length (ARL) of the control charts provides one possible basis for making this decision. The computation of ARL for the different types of control charts used in this thesis will be discussed in Chapter 4.

III. Pareto Analysis

Identifying where the problems are is the starting point in improving a process. Once these problems are identified, then suitable techniques can be applied to reduce the variation in that process. In this chapter, Pareto charts are used to identify the sources and assignable causes for variation in the air transport departure process. The primary objective is to demonstrate the use and effectiveness of this type of analysis. In addition, the use of trend charts to provide some visual information about the performance of the process will also be demonstrated. In a later part of this chapter, the author will introduce an alternative form of the Pareto chart and demonstrate its use in order to identifying the possible opportunities for improvement. Finally, the chapter concludes with some formal statistical analyses.

There are two things to consider in order to initiate the search for assignable causes. First, it is important to find suitable pivots to initially break down the whole database. Since there are different types of aircraft, this "CvsMil" pivot comes naturally to the author. "NAF" and "Mission Type" are the other two pivots that will be used as well. "Mission Type" is defined by the author. Two subgroups in it are "airlift" and "air refueling." The possible ways to break down the database are illustrated in Figure 3.1.

Second, the total number of missions within specific subgroups is another factor to consider in identifying opportunities for improvement. With a fixed budget, making the most of every penny is the requirement. Consequently, improving the process by eliminating assignable causes that are associated with a higher number of missions will be more beneficial than eliminating those associated with a smaller number of missions. For example, Table 3.1 shows the number of missions flown and three type of proportions for each type of aircraft over the time span of the data. This table suggests that the C-5 and C-141 aircraft offer the largest opportunities for improving command level performance. The two aircraft account for 60% of all

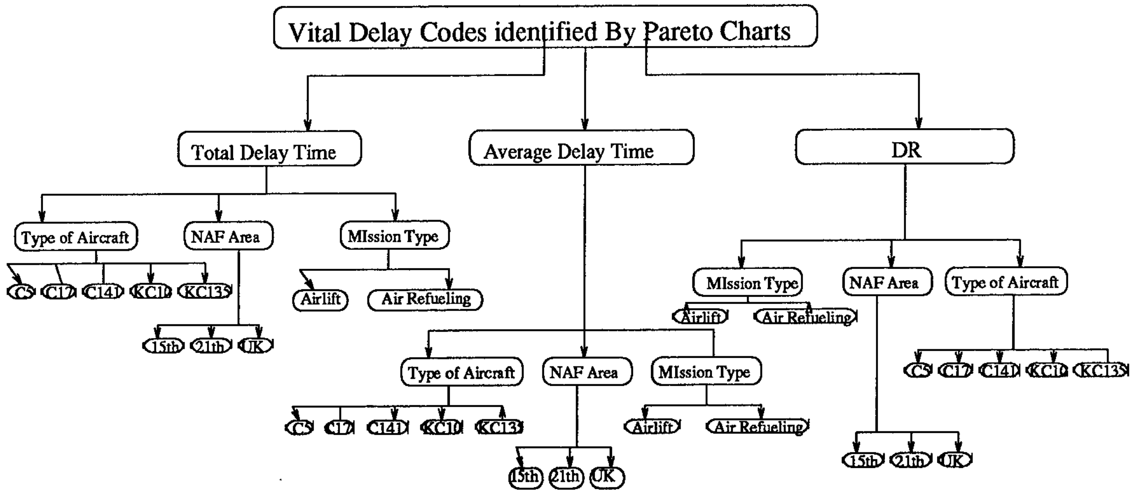


Figure 3.1 Subgroups Used in Pareto Analysis

CvsMil	Number of Missions	Proportion of Missions	Number of Delays	Proportion of Delays	DR
C-5	13783	16%	4210	25%	69%
C-17	5300	6%	615	4%	88%
C-141	37081	44%	7201	43%	81%
KC-10	8066	10%	1237	7%	85%
KC-135	20180	24%	3423	21%	83%
Total	84414	100%	16686	100%	80%

Table 3.1 The Number of Missions and Number of Delay on "CvsMil"

missions and nearly 68% of all delays. Their individual departure reliability of 69% and 81% are the worst among aircraft types.

To sum up, the best opportunity for improvement would likely be associated with the process with the worst performance in terms and with highest number of missions. To measure performance, the author will first evaluate the suitability of DR in representing AMC's performance. Secondly, total delay time (TDT) and average delay time (ADT) will be two other MOEs evaluated in this thesis.

3.1 Principle of Pareto Analysis

Pareto Analysis is an SPC tool which involves the categorization of items and the determination of which categories contain the greatest frequency of occurrence. The main objective of this technique is to find which subgroups are the vital few

and which subgroups are the trivial many. It is based on the Pareto principal which, as applied to quality improvement, stated that a large proportion of process variability can be attributed to relatively few cause. Pareto analysis is used in industry as a problem identification tool. Specifically, the vital few causes that contribute the most to process variability are candidates for being treated as assignable causes, since it is most likely that these cause can be detected, identified and eliminated. The trivial many causes that contributes the least to process variability are usually treated as chance causes.

The primary tool of Pareto analysis is the Pareto Chart which is simply a relative frequency histogram of bar chart, with the bars arranged in descending order of height from left to right across the horizontal axis.

Except for the UK subgroup under the "NAF area," the author developed Pareto charts to identify the top 19 vital delay codes within each subgroup of the data examined. (The reason for this exception is because the subgroup "UK" does not have as many missions as the 15th and 21st do. The author only picked the top 5 delay codes for this subgroup.) Each identified delay code is represented by a number in the Pareto charts. Based on AMC's information, there are a total of 182 delay codes that are used to classify all departure delays into accountable agencies or delay code categories. When the top delay codes are identified by numbers, the author will provide tables to list what the delay codes numbers stand for.

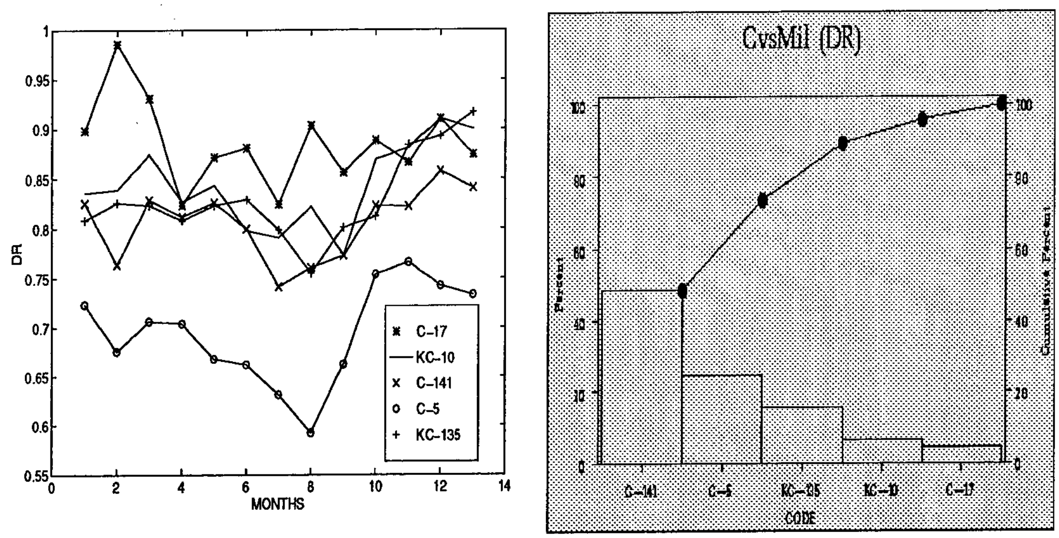
The last bar or right-hand most bar in each Pareto chart represents the proportion of the rest of the delay codes, which are considered as the trivial many. The bigger this bar is, the less representative the vital few are, and vice versa. In the Pareto charts, the horizontal axis lists all vital subgroups. The left vertical axis can be assigned either the percentage or frequency of the measurement characteristic as scale for the subgroups, the right vertical axis is fixed to represent a cumulative percentage. The line cross the horizontal direction shows the amount of this cumulative percentage.

		MOE		
Pivot	**subgroup**	**DR**	**ADT**	**TDT**
	C-5	Subsection 3.21	Subsection 3.22	subsection 3.23
	C-17	Appendix A	Appendix A	Appendix A
CvsMil	C-141	Subsection 3.21	Subsection 3.22	Subsection 3.23
	KC-10	Appendix A	Appendix A	Appendix A
	KC-135	Appendix A	Appendix A	Appendix A
	15th	Appendix A	Not Included	Appendix A
NAF	21th	Subsection 3.31	Not included	Subsection 3.33
	UK	Appendix A	Not Included	Appendix A
Mission	Lift	Subsection 3.41	Subsection 3.42	Subsection 3.43
Type	Refuel	Appendix A	Appendix A	Appendix A

Table 3.2 Location of Results of Pareto Charts

There are some delay codes identified by Pareto Charts that can not be verified by the information on hand because there are no explanations to define them. The author put "unknown" in the description field for delay associated with these codes. The author used subgroups shown in Figure 3.1 to apply Pareto charts as a problem identifying technique for the complete dataset. However, only the Pareto charts, and their corresponding delay code tables, associated with the C-5, C-141, 21st NAF and airlift missions are discussed in this Chapter. Charts and tables for the remaining subgroups are in Appendix A. Table 3.2 indicates this arrangement, where the first column lists the pivots and second column describes the subgroups under each pivot.

The MRO has used Pareto charts extensively to describe the number of delays incurred with respect to specific delay codes. For the sake of completion and comparison, this thesis will conduct a similar analysis but also apply Pareto analysis using different MOEs. Details will be presented as follows.



(a) (b)

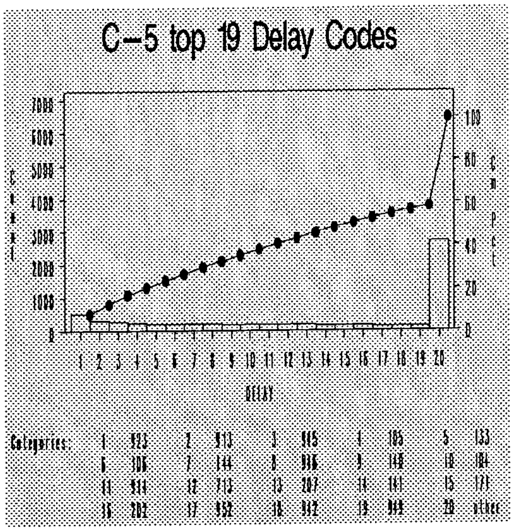
Figure 3.2 (a) DR Trend Chart (b) DR Pareto Chart

3.2 Identifying Opportunities for Improvement By Aircraft Type

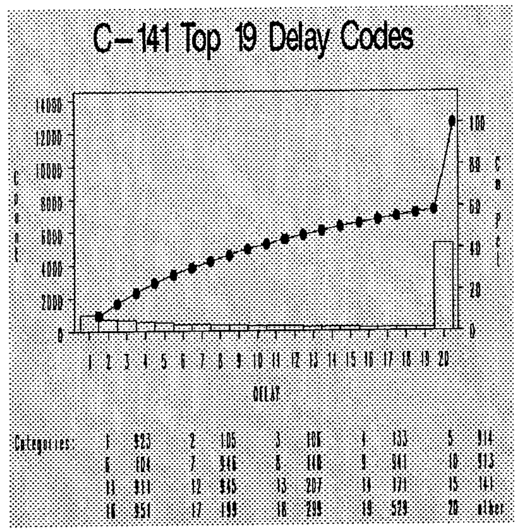
In the following subsections, each of the three MOEs (DR, ADT, TDT) will be used to identify the possible assignable cause or source of variation that contribute the most to the observed variability in departure delays according to aircraft type.

3.2.1 Results Using DR as an MOE. In this section, the author uses trend charts to provide visual information about DR performance over time and then use the Pareto charts to identify the possible source of variation. Figure 3.2 part (a) is the trend chart. The plotting points in this figure are the monthly DRs for each type of aircraft. This chart shows that the C-17 has the highest DR, and the C-5 has the lowest DR. The ranks of the others are not clear in this trend chart.

Figure 3.2, part (b) displays the corresponding Pareto charts. The measurement characteristic in this chart is the number of departure delays for each type of aircraft. The C-141 subgroup has the largest number, and the C-5 is in second place. In terms of SPC terminology, these two are candidates for the vital few; the rest of the subgroups may represent the trivial many. These first two subgroups accumulate



(a)



(b)

Figure 3.3 Pareto Charts on DR Against Delay Codes for the (a) C-5 (b) C-141

almost 80 percent of the total number of delays. As mentioned earlier, the number of missions for each type of aircraft also needs to consider in this assessment. Based on Table 3.1, these two also have the heaviest duty. Thus, they provide the greatest opportunities for improvement.

Having focused attention on these two aircraft, the author then developed additional Pareto charts for these two subgroups. Figure 3.3 shows Pareto charts for the C-5 and C-141 aircraft which depict the number of occurrences of delay by delay code. The author identified the top 19 delay codes as the primary candidates for the vital few. Tables 3.3 explains what these delay codes represent for both subgroup processes. These last two Pareto Charts are somewhat disappointing since they do not identifying a small number (say four or five) delay codes as accounting for most of the delays. Instead, the 19 top delay codes (roughly 10 percent of all delay codes) account for less than 60 percent of all delays. This suggests that the causes for delay are many and varied with few “quick fixes” leaping into view.

Rank	C-5 DR Delay Code & Description	C-141 DR Delay Code & Description
1	923:Power Plant	923:Power Plant
2	913:Landing gear	105:en route weather
3	945:Hydraulic and Pneumatic power supply	106:Arrival station weather precluded a safe landing
4	105: en route weather	133:ATC delay
5	133:ATC delay	914:Flight controls
6	106:Arrival station Weather preluded safe landing	104:Precluded Take off
7	144:MOG	946:Fuel Systems
8	946: Fuel System	140:Departure Station restricted
9	140:Departure station restriction	941:Air conditioning
10	104:Preclude takeoff	913:Landing Gear
11	914:Flight control	911:Airframe structure and windows
12	713:Stock level has not been established	945:Hydraulic and pneumatic power supply
13	207:Crew duty insufficient	207:Crew duty time insufficient
14	141:Arrival station restricted	171:Load improperly configured
15	171:Load improperly configured	141:Arrival Station Restricted
16	202:Crew rest	951:Instrument systems
17	952:Automatic flight control	199:Miscellaneous Deviation
18	942:Electrical power supply	299:Other operation deviation
19	949:Misc.utilities/fire station	529:other management deviation

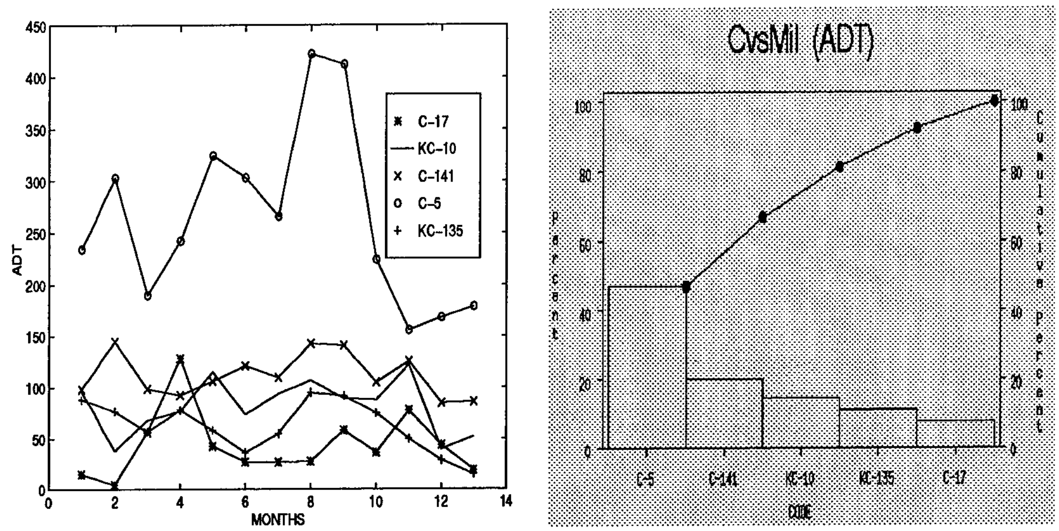
Table 3.3 The Top 19 Delay Codes for the C-5 and C-141 Aircraft (DR)

3.2.2 Results Using Average Delay Time as an MOE. Figure 3.4, part (a) displays the trend chart for ADT by aircraft type. The plotting points here are the monthly ADT for each type of aircraft. It shows that the C-5 clearly has the biggest ADT over time; the C-141 and KC-135 are close to each other. From the trend chart, it is hard to tell which is the second largest. Thus, we need some help from the Pareto charts.

Figure 3.4, part (b) is the Pareto chart to identify the aircraft types accounting to the largest proportions of average delay time. The measurement characteristic here is the ADT for each type of aircraft. From this chart, it is clear the C-5 and C-141 subgroups are the two that make the most contribution to the overall ADT. As we notice, these two accumulate almost 70 percent of the overall MOE.

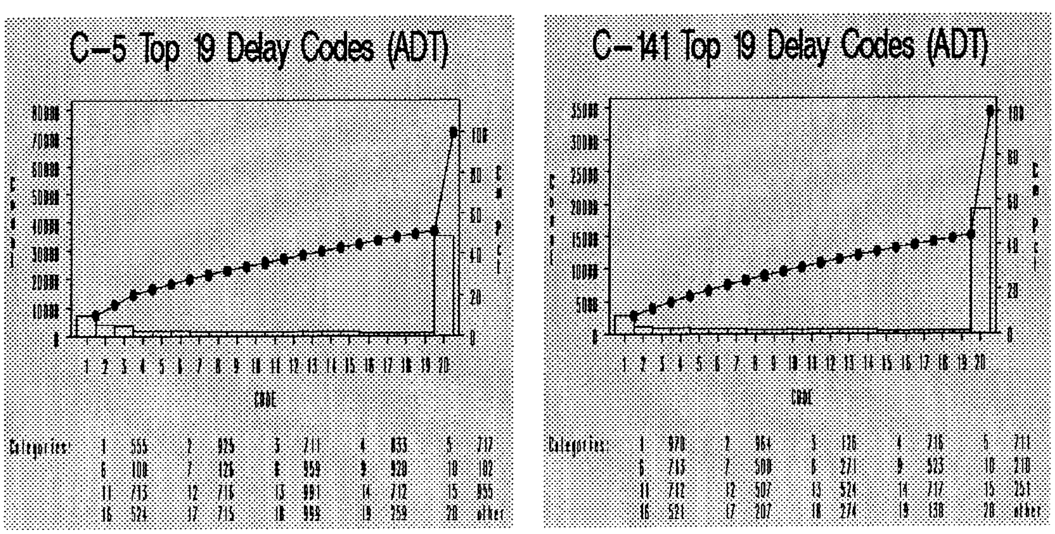
As with DR, the author then applied the Pareto charts again on these two subgroups identifying the top 19 delay codes. Figure 3.5 shows the C-5 and C-141 processes in terms of this MOE. Table 3.4 shows what the corresponding delay codes are for both processes. Note that the top 19 delay codes barely account for half all delays when measured against this MOE.

3.2.3 Results Using Total Delay Time as an MOE. Figure 3.6, part (a) is the trend chart which monitors the monthly TDT for each type of aircraft. Five



(a) (b)

Figure 3.4 (a) ADT Trend Chart (b) ADT Pareto Chart



(a) (b)

Figure 3.5 Pareto Charts on Average Delay Time Against Delay Codes for the (a) C-5 (b) C-141

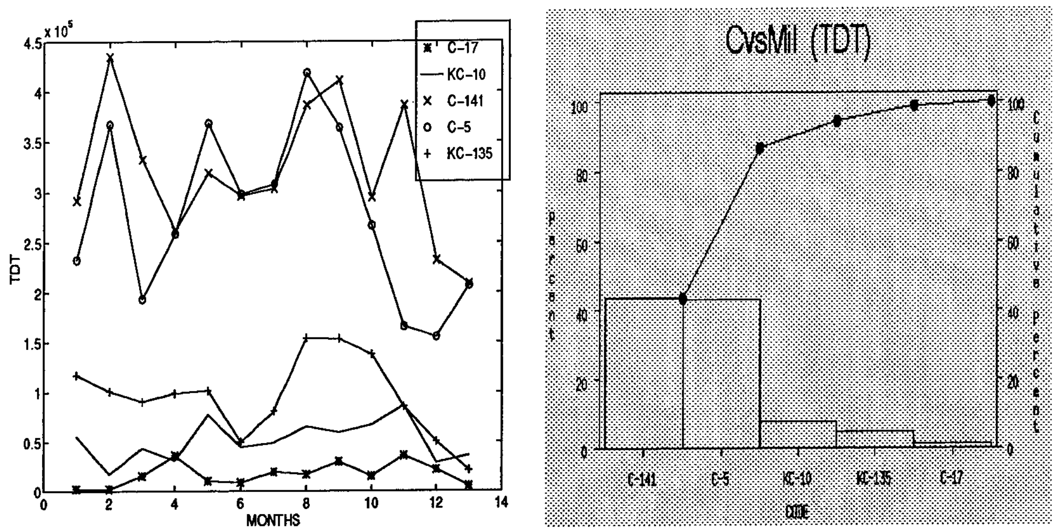
	C-5 Delay Codes Identified by Average Delay Time	C-141 Delay Codes Identified by Average Delay Time
Rank	Delay Code&Description	Delay Code&Description
1	555:Deviation Unresolved	970:Unknown
2	925:Unknown	964:Intercom
3	711:Requested Exceeds authorized level	126:Supply
4	833:Saturation of shortage of support equipment	716:Order and ship time
5	717:Supply issued the wrong part	711:Requested exceeds authorized level
6	100:No alternative available	713:Stock level to maintain this aircraft, but item not listed
7	126:Supply	500:Unknown
8	959:Refueling system	271:Awaiting diplomatic clearance
9	920:Unknown	523:Deviation directed to support higher priority mission
10	102:Inspection ot repaired weather related damage	210:Crew availability
11	713:Stock level maintain this type of aircraft, item not listed	712:Stock level not maintain this aircraft
12	716:Order and ship time exceeds	507:Sympathetic delay
13	991:Emergencies	524:Deviation directed to match home station air crew
14	712:Stock level not maintain this type of aircraft	717:Supply issued the wrong part
15	955:Madras and History/flight data, and so on	251:Unknown
16	524:Deviation directed to match home station and aircrew	521:Deviation directed to support USAF, JCS
17	715:Order and ship time not exceed	207:Crew duty time insufficient
18	999:Other logistics Maintenance deviation	274:Required ground support equipment
19	259:Stage crew management error	130:Held for quarantine

Table 3.4 The Top 19 Delay Codes for the C-5 and C-141 Aircraft (ADT)

curves form two groups in this trend chart. It is hard to tell the difference within the groups. However, the C-5 and C-141 aircraft belong to the group that has the worst performance. The C-17 seems to have the lowest TDT most of the time. From the Pareto chart's perspective, in Figure 3.6, part (b), the C-141 accounts for a higher proportion of TDT than the C-5; however, they are really close to each other.

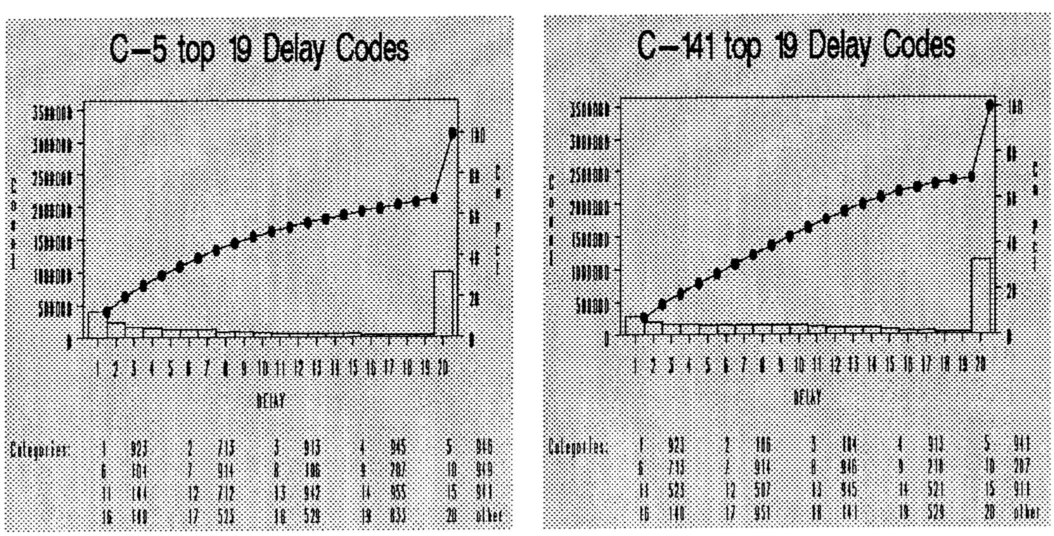
Again, once these target aircraft types were identified, the author applied Pareto charts to these two subgroups. Figure 3.7 shows the Pareto charts for the C-5 and C-141 processes in terms of TDT. The measurement characteristics here are the overall TDTs for each delay code over a 13-month period. Top 19 delay codes are displayed. Table 3.5 is the corresponding table to show what the corresponding delay codes are. Note that the top 19 delay codes account for almost 70% of the total delay time, which is more like we had hoped to find using this sort of analysis. Still, although "power plant" is seen as the largest source of delay, few quick fixes are suggested.

3.2.4 Further Analysis by Aircraft Type. Based on the results so far, we notice that the three different MOEs each identify the C-5 and C-141 as the aircraft which contribute most to delays. This suggests that the three MOEs have similar ability in identifying possible starting points for improvement. However, when we



(a) (b)

Figure 3.6 (a) TDT Trend Chart(b) TDT Pareto Chart



(a) (b)

Figure 3.7 Pareto Charts on Total Delay Time Against Delay Codes for the (a) C-5 (b) C-141

	C-5 Total Delay Time	C-141 Total Delay Time
Rank	Delay Code & Description	Delay Code & Description
1	923:Power Plant	923:Power Plant
2	713:Stock level maintain this aircraft, not established this item	106:Arrival station weather precluded a safe landing
3	913:Landing gear	104:Precluded Take off
4	945:Hydraulic and pneumatic power supply	913:Landing Gear
5	946:Fuels system	941:Air conditioning
6	104:Precluded take off	713:Stock level maintain this aircraft, not established this item
7	914:Flight control	914:Flight control
8	106:Arrival station weather precludes a safe landing	946:Fuel system
9	207:Crew duty time insufficient	210:Crew availability
10	949: Misc. utilities	207:Crew duty time insufficient
11	144:MOG restricted	523:Deviation directed to support higher priority mission
12	712:Stock level does not maintain this type of aircraft	507:Sympathetic delay
13	942:Electronic power supply	945:Hydraulic and pneumatic power supply
14	955:MADAR and history	521:Deviation directed by USAF, JCS, state department
15	941:Air conditioning	911:Airframe structure and windows
16	140:Departure station restriction	140:Departure station restriction
17	523:Deviation directed to support higher priority mission	951:Instrument/Independent system
18	529:Other management deviation	141:Arrival station restrictions
19	833:Saturation ot shortage of support equipment	529:other management deviation

Table 3.5 Delay Codes for the C-5 and C-141 Aircraft (TDT)

examine the individual delay code for each type of aircraft, different delay codes are identified, suggesting that each MOE brings a unique perspective to the analysis. Of these, DR and TDT would appear to be the most useful.

For example, consider the Pareto charts for the C-5 aircraft, it is interesting to note that the three MOEs share only one delay codes (number 713) among their top 10. On the other hand, DR and TDT share 10 delay codes out of their top 19 (code 923, 913, 945, 946, 104, 914, 106, 144, 942, and 140). This sort of behavior should not be surprising since a single long delay can produce a large ADT for a particular delay code but would not be expected to provide strong influence on either DR or TDT. The latter MOEs are, instead functions of the total number of delays of a particular type. It would thus appear that ADT is not very useful in identifying opportunities for improvement while DR and TDT might be. Of the latter, TDT might be the more revealing since it accounts for delay time as well as the number of delays. The proceeding Pareto analysis were slightly disappointing because they did not immediately identify a small number of delay codes as responsible for a large proportion of the variation in the departure process. This perhaps suggests that we used to fine a mesh in categorizing delays. As a result, the author next categorized delay codes in terms of "delay code categories" and "accountable agencies." Table 3.6 and 3.7 are the comparison tables in terms of "delay code categories." Tables

order	Category	Accountable Agency	DR	ADT	TDT
1	Weather	AMC(DO)	3	2	2
2	Events and Incidents	AMC(SP), NAF, AMC(DO)	0	0	0
3	Host Base Support(at AMC bases)	NAF	0	1	0
4	Host Base Support(at Non-AMC bases)	AMC(SV,LG,DO)	0	0	0
5	External Agencies	AMC(DO)	1	0	0
6	Airfield	AMC(DO), NAF	3	0	2
7	Contract Carrier Controllable	AMC(DO)	0	0	0
8	User	AMC(DO)	1	0	0
9	Aeromedical Evacuation (Medical Support (Non-AMC)	AMC(SG)	0	0	0
10	Aeromedical Evacuation (Medical Support AMC	NAF	0	0	0
11	Aircrew	AMC(DO), NAF	2	0	1
12	Management and Coordination	NAF	0	1	0
13	Unit Planning	NAF	0	0	0
14	Other	AMC(DO)	0	0	0
15	Management	NAF	0	1	0
16	Passenger Service	NAF	0	0	0
17	Air Freight	NAF	0	0	0
18	Fleet Service	NAF, AMC(DO)	0	0	0
19	Execution	TACC	0	0	0
20	Planning	TACC	0	0	0
21	Management	TACC	0	1	2
22	Logistics Deviation Indicators Supply	AMC(LG), NAF	1	6	2
23	Logistics Deviation Indicators Saturation ot shortage	NAF, AMC(LG)	0	1	1
24	Airframe	NAF	2	0	2
25	Power Plant	NAF	1	0	1
26	System	NAF	5	3	6
27	other	NAF	0	1	0
28	unknown		0	2	0

Table 3.6 The Comparison of Accountable Delay Categories Between DR, ADT and TDT for the C-5 Aircraft

3.8 and 3.9 are the comparison tables in terms of "accountable agencies." Based on AMC's regulations, all delay codes are divided into 27 items under "delay code categories" and 7 "accountable agencies." Since some of the vital delay codes can not be categorized using the information provided by AMC, the author put these into an "unknown " category. These categories are listed in the second column of Table 3.6. The third column describes the corresponding accountable agencies. As to columns 4 to 6, numbers in the cells represent the number of occurrences in each category under the different MOEs. Similar explanations extend to the tables for the C-141 subgroup, Table 3.7.

The author developed the Pareto charts by "accountable delay categories" to demonstrate the possible suitability of this grouping factor. The results are shown in Figure 3.8.

From a "delay code categories" perspective, "system" is the most frequently occurring category for DR and TDT while ADT identifies the "logistics deviation Indicator supply" as its largest category. Consequently, this categorizes assignable

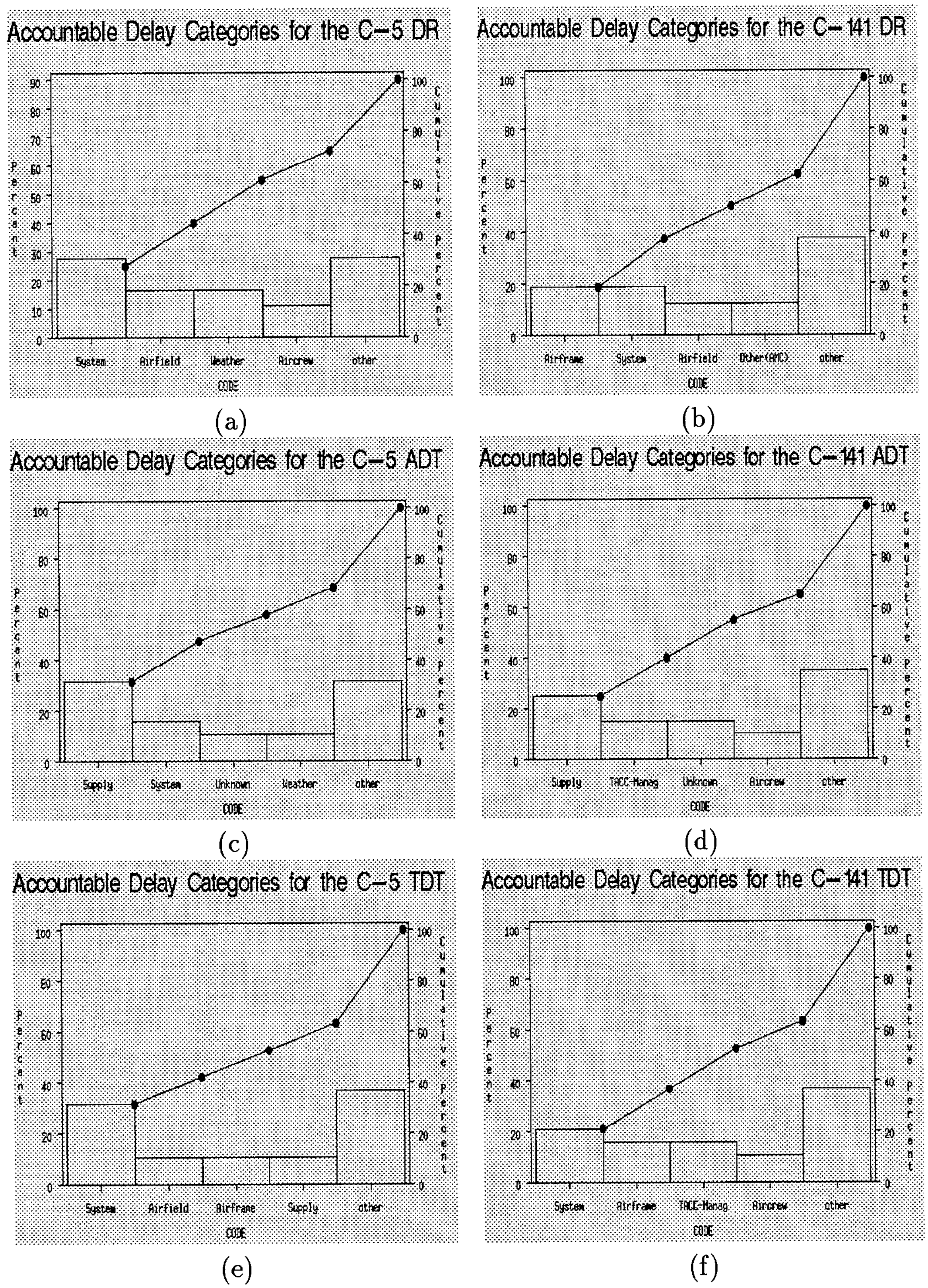


Figure 3.8 Pareto Charts for the Accountable Delay Categories: (a)C-5 DR (b)C-141 DR (c)C-5 ADT (d) C-141 ADT (e) C-5 TDT (f) C-141 TDT

order	Category	Accountable Agency	DR	ADT	TDT
1	Weather	AMC(DO)	2	0	2
2	Events and Incidents	AMC(SP), NAF, AMC(DO)	0	0	0
3	Host Base Support(at AMC bases)	NAF	0	1	0
4	Host Base Support(at Non-AMC bases)	AMC(SV,LG,DO)	0	0	0
5	External Agencies	AMC(DO)	1	0	0
6	Airfield	AMC(DO), NAF	2	0	2
7	Contract Carrier Controllable	AMC(DO)	0	0	0
8	User	AMC(DO)	1	0	0
9	Aeromedical Evacuation (Medical Support (Non-AMC)	AMC(SG)	0	0	0
10	Aeromedical Evacuation (Medical Support AMC	NAF	0	0	0
11	Aircrew	AMC(DO), NAF	1	2	2
12	Management and Coordination	NAF	0	1	0
13	Unit Planning	NAF	0	2	0
14	Other	AMC(DO)	2	0	0
15	Management	NAF	0	1	0
16	Passenger Service	NAF	0	0	0
17	Air Freight	NAF	0	0	0
18	Fleet Service	NAF, AMC(DO)	0	0	0
19	Execution	TACC	0	1	1
20	Planning	TACC	0	0	0
21	Management	TACC	1	3	3
22	Logistics Deviation Indicators Supply	AMC(LG), NAF	0	5	1
23	Logistics Deviation Indicators Saturation ot shortage	NAF, AMC(LG)	0	0	0
24	Airframe	NAF	3	0	3
25	Power Plant	NAF	1	0	1
26	System	NAF	3	1	4
27	other	NAF	0	0	0
28	unknown		0	3	0

Table 3.7 The Comparison of Accountable Delay Categories Between DR, ADT and TDT for the C-141 Aircraft

causes in maintenance types or logistics types of problems. However, this does not provide an obvious approach to improving these types of problems. The author does not have the appropriate information to make further assessments. Although, perhaps one could gain insight by doing a Pareto analysis by delay codes within those largest categories.

Based on AMC's regulations, "accountable agencies" is another grouping factor. To the author, this factor could also be an approach to group the MOEs. The author also developed Pareto charts for the top 19 delayed codes. The Pareto charts of the C-5 and C-141 aircraft for this grouping factor is shown in Figure 3.9. The measurement characteristics in these charts are the number of frequencies of the vital 19 delay codes occurred in the corresponding accountable agencies. Note that in these charts, the proportions of the vital few are over at least 60% or more of the measurement characteristics.

When the pivot is the "CvsMil", the DR and TDT tend to identify AMC(DO) and NAF as accountable agencies. ADT tends to identify AMC(LG) and NAF.

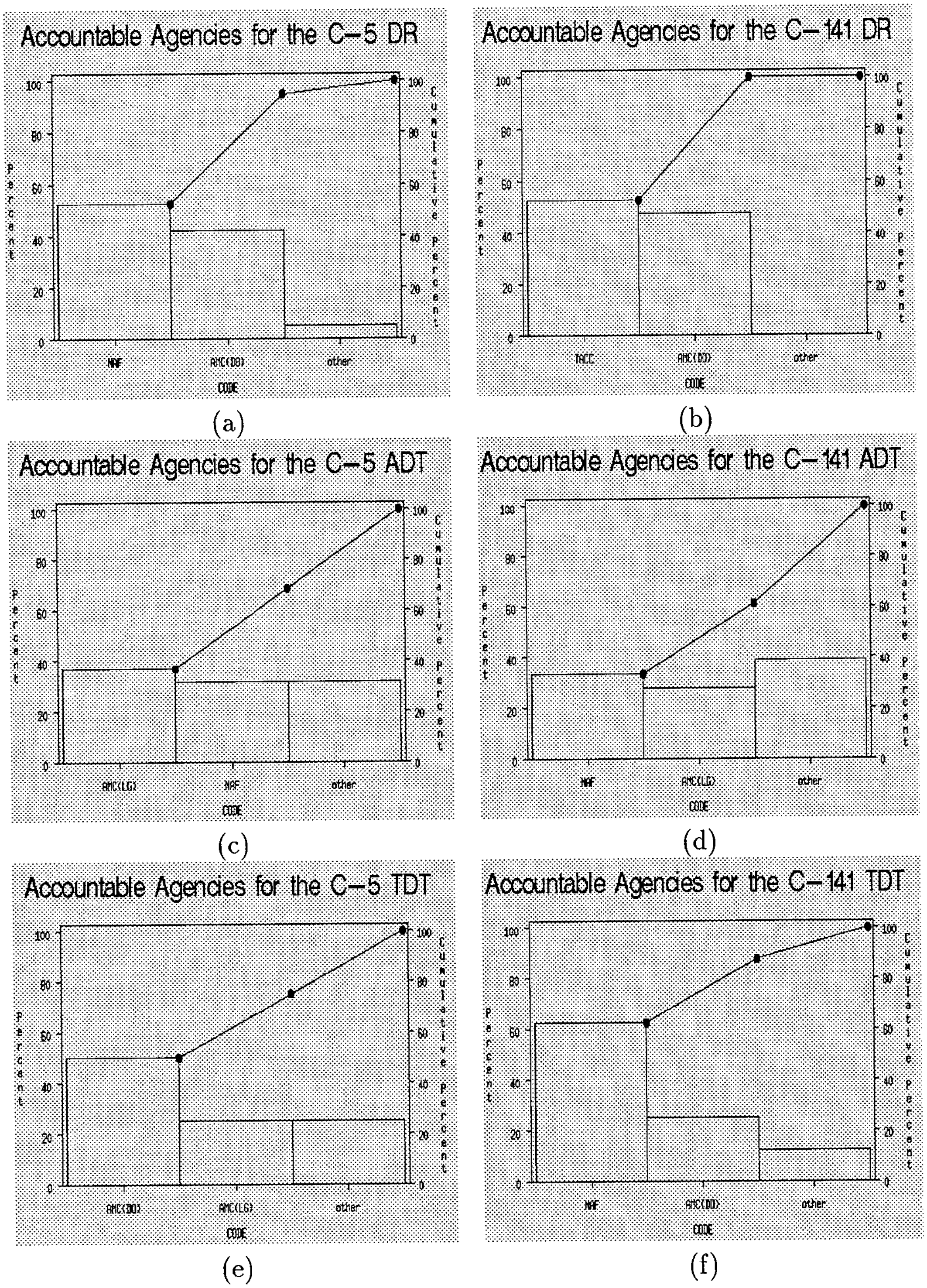


Figure 3.9 Pareto Charts for the Accountable agencies: (a)C-5 DR (b)C-141 DR (c)C-5 ADT (d) C-141 ADT (e) C-5 TDT (f) C-141 TDT

Order		DR		ADT		TDT	
	Accountable Agencies	frequency	Percentage	frequency	Percentage	frequency	Percentage
1	AMC(DO)	8	.421	2	.105	4	.210
2	AMC(LG)	1	.052	7	.368	2	.105
3	AMC(SG)	0	0	0	0	0	0
4	AMC(SP)	0	0	0	0	0	0
5	AMC(SV)	0	0	0	0	0	0
6	NAF	10	.526	6	.315	11	.578
7	TACC	0	0	2	.105	2	.105
8	Unknown	0	0	2	.105	0	0

Table 3.8 The Comparison of Accountable Agencies Between DR, ADT and TDT for the C-5 Aircraft

Order		DR		ADT		TDT	
	Accountable Agencies	frequency	Percentage	frequency	Percentage	frequency	Percentage
1	AMC(DO)	9	.473	1	.052	4	.210
2	AMC(LG)	0	0	5	.263	1	.052
3	AMC(SG)	0	0	0	0	0	0
4	AMC(SP)	0	0	0	0	0	0
5	AMC(SV)	0	0	0	0	0	0
6	NAF	10	.526	6	.315	10	.526
7	TACC	0	0	4	.210	1	.210
8	Unknown	0	0	2	.157	0	0

Table 3.9 The Comparison of Accountable Agency Between DR, ADT and TDT for the C-141 Aircraft

Consequently, DR and TDT have the similar perspective under the pivot "CvsMil." Tables 3.8 and 3.9 summarize the results for the C-5 and C-141 aircraft.

The grouping factor, like "accountable delay categories" or "accountable agencies," can be actually considered as pivots to break down the whole database. Both of these seem to be rational pivots. It is believed that some interesting insights can be gained by doing that. However, the pivot table function does not support these two, it will be quite time-consuming to classify the whole database based on these two factors without computer's support. Thus, the author only classified the top 19 vital delay codes from Pareto charts to demonstrate the use.

3.3 Identifying Opportunity for Improvement by "NAF"

In this section, the author will follow the same methodology conducted in the previous section except for not using the trend chart (Trend charts are omitted since they were not seen to be very informative). The author picked "NAF area" as a pivot to break down the whole database. The purpose is to determine whether or

CvsMil	The Number of Missions	Proportion of Missions	Number of Delays	Proportion of Delays	DR
15th	36781	43.6%	6391	38.2%	83%
21st	47412	56.1%	10267	61.4%	78%
UK	221	0.3%	47	0.3%	79%
Total	83245	100%	16705	20%	80%

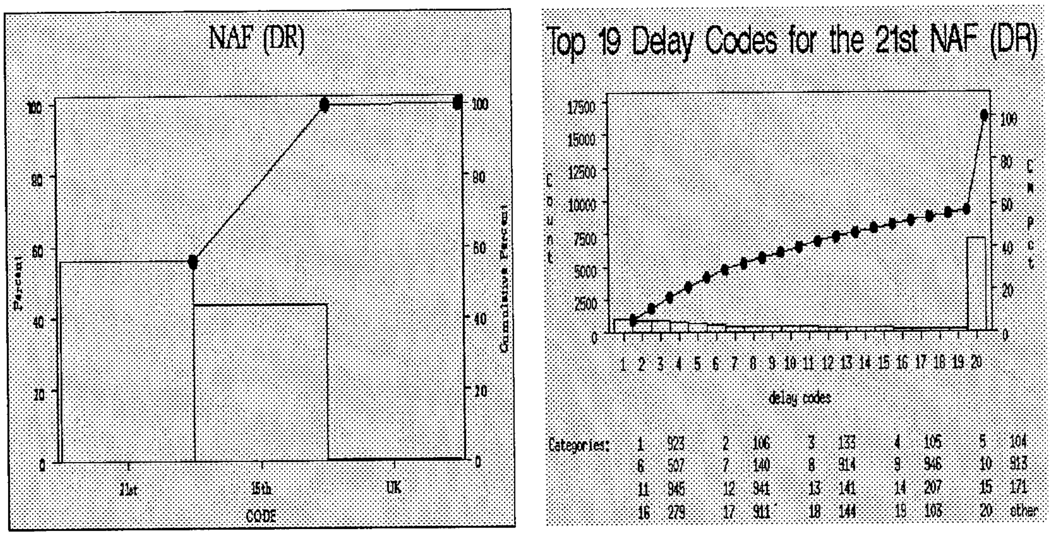
Table 3.10 The Number of Missions and Number of Delays on "NAF area"

not this categorization of the data leads to a fruitful identification of some vital few areas for improvement.

There are three subgroups under this pivot. The author will develop the Pareto charts using the three different MOE to demonstrate the effectiveness of them. Table 3.10 lists the the number of missions and different type of proportions for each subgroup. This table suggests that the 21st NAF offers the largest opportunity for improvement since this NAF accounts almost 56% of all missions and 61% of all delays. On the other hand, there is not a substantial difference between the 15th and 21st NAF. The UK NAF is clearly different since it accounts for relative few missions.

3.3.1 Results Using DR as an MOE. Figure 3.10, part (a) displays the Pareto chart of NAF subgroups, where the measurement characteristic is the number of occurrences of delays for each subgroup. The results show that the 21st NAF takes the top one position. Because there are only three subgroups, the author only picked this one target subgroup to demonstrate the usage of subsequent Pareto Charts. The 21st NAF also has the heaviest duty. Consequently, this provides the largest opportunity for improvement.

Figure 3.10, part (b) shows the Pareto chart for the number of delay code occurrences for each delay code while Table 3.11 lists the descriptions for those delay codes. Note that the top 19 delay codes account for about 55% of the total number of delays experienced.



(a) (b)

Figure 3.10 (a) NAF Pareto Chart (DR) (b) Pareto Charts for the 21st NAF (DR)

	Delay Codes Identified by DR	
Rank	**Delay Code**	**Description**
1	923	Power plant
2	106	Arrival station weather precluded a safe landing
3	133	ATC delay
4	105	En route weather
5	104	Precluded take off
6	507	Sympathetic delay
7	140	Departure station restriction
8	914	Flight control
9	946	Fuel system
10	913	Landing gear
11	945	Hydraulic and pneumatic power supply
12	941	Air conditioning
13	141	Arrival station restriction
14	207	Crew duty time insufficient
15	171	Load improperly
16	279	Deviation required due to scheduling error
17	911	Air frame structure and windows
18	144	MOG
19	103	Precluded ground process of aircraft

Table 3.11 The 21st NAF Vital Delay Codes Identified by DR

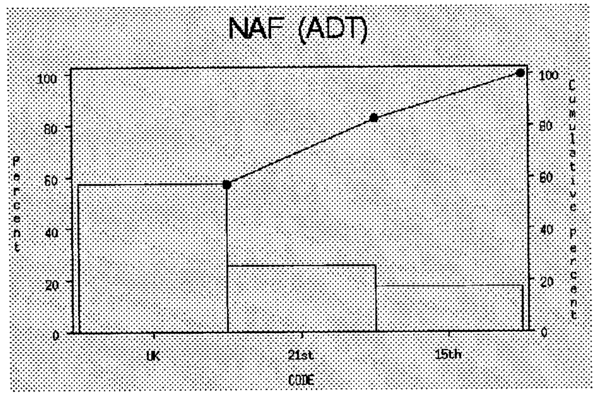
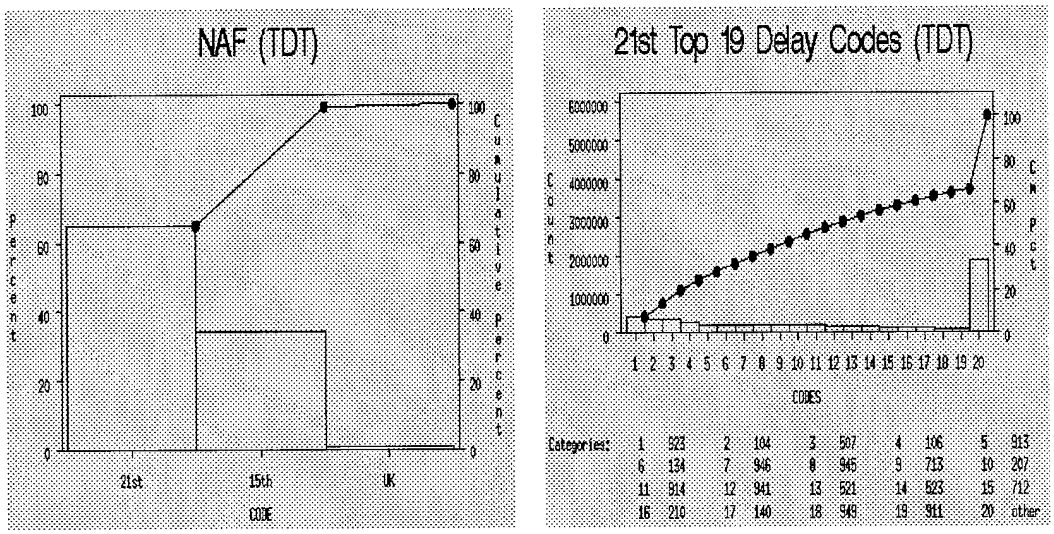


Figure 3.11 NAF Pareto Chart (ADT)

3.3.2 Results Using Average Delay Time as an MOE. This time, we use ADT as the MOE. Figure 3.11 demonstrates what the Pareto chart looks like. It is interesting that the "UK' subgroup is the largest now! On the surface, that means the UK NAF appeared to be the most important subgroup contributing the most to the total variation observed. However, there are only 221 UK missions over that time period, which is a trivial number compared to the other two NAFs. In other words, the use of average delay time is not very meaningful in this case. That is, as noted earlier, when the numbers of missions for differ greatly between subgroups, attention should be paid to the number of observations within each subgroup.

3.3.3 Results Using Total Delay Time as an MOE. The author also developed a Pareto chart using TDT as the MOE and presents this as Figure 3.12, part (a). The measurement characteristic here is the TDT for each of the subgroups over a 13 month period. The results show that 21st NAF is the number one choice.

As usual, the author applied Pareto chart on this group shown in Figure 3.12, part(b). The measurement characteristic in this figure is the TDT for each delay code over the 13 month period. Table 3.12 shows what the vital delay codes are.



(a) (b)

Figure 3.12 (a) NAF Pareto Chart (TDT) (b) Pareto Charts on Total Delay Time Against Delay Codes for 21st NAF

	Delay Codes Identified by Average Delay Time	
Rank	**Delay Code**	**Description**
1	923	Power plant
2	104	Precluded takeoff
3	507	Sympathetic delay
4	106	Arrival station weather precluded a safe landing
5	913	Landing gear
6	134	Non receipt of diplomatic clearance
7	946	Fuel System
8	945	Hydraulic and pneumatic power supply
9	713	Stock level maintain, but the item is not listed
10	207	Crew duty time insufficient
11	914	Flight control
12	941	Air conditioning
13	521	Deviation directed to ot validate to USAF, JCS, SD
14	523	Deviation directed to support higher priority mission
15	712	Stock Levels not maintain for this aircraft
16	210	Crew availability
17	140	Departure station restriction
18	949	Misc. utility
19	911	Airframe structure and window

Table 3.12 The 21st NAF Vital Delay Codes Identified by Total Delay Time

order	Category	Accountable Agency	DR	ADT	TDT
1	Weather	AMC(DO)	4	0	2
2	Events and Incidents	AMC(SP), NAF, AMC(DO)	0	0	0
3	Host Base Support(at AMC bases)	NAF	0	1	0
4	Host Base Support(at Non-AMC bases)	AMC(SV,LG,DO)	0	0	0
5	External Agencies	AMC(DO)	1	1	2
6	Airfield	AMC(DO), NAF	3	0	0
7	Contract Carrier Controllable	AMC(DO)	0	0	0
8	User	AMC(DO)	1	0	0
9	Aeronautical Evacuation (Medical Support (Non-AMC)	AMC(SG)	0	0	0
10	Aeromedical Evacuation (Medical Support AMC	NAF	0	0	0
11	Aircrew	AMC(DO), NAF	1	0	2
12	Management and Coordination	NAF	0	1	0
13	Unit Planning	NAF	1	1	0
14	Other	AMC(DO)	0	0	0
15	Management	NAF	0	0	0
16	Passenger Service	NAF	0	0	0
17	Air Freight	NAF	0	0	0
18	Fleet Service	NAF, AMC(DO)	0	0	0
19	Execution	TACC	1	0	1
20	Planning	TACC	0	0	0
21	Management	TACC	0	4	2
22	Logistics Deviation Indicators Supply	AMC(LG), NAF	1	7	2
23	Logistics Deviation Indicators Saturation ot shortage	NAF, AMC(LG)	0	0	0
24	Airframe	NAF	3	0	3
25	Power Plant	NAF	1	0	1
26	System	NAF	3	5	4
27	other	NAF	0	0	0
28	unknown		0	2	0

Table 3.13 The Comparison of Accountable Delay Categories Between DR, ADT and TDT for the 21st NAF

3.3.4 Further Analyses by NAF. Based on the results in this section, DR and TDT all identify the 21st NAF as the numbered air force which contributes most to delays. This again indicates that TDT has similar ability in identifying possible starting points for improvement. When we examine individual delay codes for each NAF, these two MOE still maintain their own perspectives. However, they share 12 delay codes out of their top 19 with different ranks (code 923, 106, 104, 501, 140, 914, 946, 913, 945, 941, 207, and 911). Unfortunately, there is still no dominate delay codes found in this pivots. The author again developed Pareto charts for delay codes category. From a "delay code category" perspective, "system" is the most frequently occurring category based on the 26th row in Table 3.13. ADT tends to imply the importance of "Logistics deviation Indicator supply." The "accountable agencies" is not suitable in this context because 21st NAF has already been hold as an accountable agency.

Mission Type	The Number of Missions	Proportion of Missions	Number of Delays	Proportion of Delays	DR
Airlift	56164	67%	12026	72%	79%
Air refueling	28250	33%	4660	28%	84%
Total	84414	100%	16686	100%	80%

Table 3.14 The Number of Missions and Number of Delays on "Mission Type"

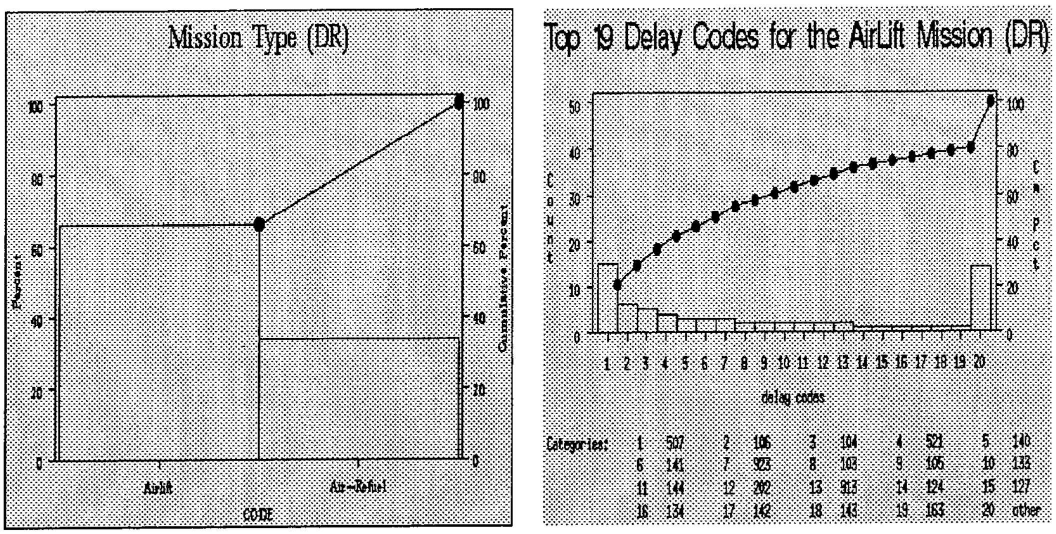
3.4 Identifying Opportunity for Improvement by "Mission Type"

This section takes the pivot "mission type" grouped by the author. The two subgroups are "airlift" and "air refueling." Mission performed by the C-5, C-17 and C-141 makes up "airlift" subgroup while those performed by the KC-10 and KC-135 aircraft form the "air refueling" subgroup. These groupings were selected in an attempt to determine if this categorization would enable opportunity for improvement to be more readily identified. Table 3.14 lists the number of missions and different type of proportions for these subgroups.

3.4.1 Results Using DR as an MOE. Figure 3.13, part (a) shows the target groups categorized by a Pareto chart in terms of DR. The measurement characteristic in this figure is the number of departure delays over the 13 month period. The airlift group clearly dominate the air refueling subgroup. Thus, airlift subgroup is picked for further analysis. Figure 3.13, part (b) demonstrates this. The measurement characteristic here is the number of the delayed departures.

Table 3.15 lists the corresponding delay codes. It is interesting to note that the top 19 delay codes now account for 70% of the delay, more like what we typically expect in a Pareto analysis. Sympathetic delay alone accounts for over 15% of all delays, suggesting that this would be a fruitful area of investigation in a hunt for assignable causes.

3.4.2 Results Using Average Delay Time as an MOE. Likewise, the author developed a Pareto chart in terms of ADT as shown in Figure 3.14, part (a). Airlift missions still dominate air refueling mission. Figure 3.14, part (b) demonstrates the

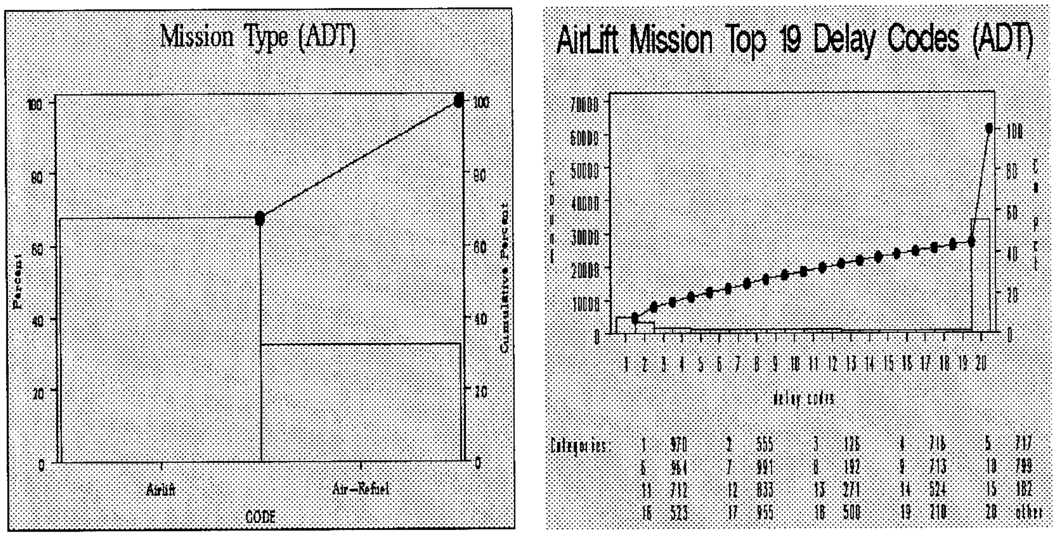


(a) (b)

Figure 3.13 (a) DR Mission Type Pareto Chart (b) Airlift Pareto Charts for DR

	Delay Codes Identified by DR	
Rank	**Delay Code**	**Description**
1	507	Sympathetic delay
2	106	Arrival station weather precluded a safe landing
3	104	Precluded take off
4	521	Deviation directed to ot validate to USAF, JCS, SD
5	140	Departure station restriction
6	141	Arrival station restriction
7	923	Power plant
8	103	Precluded ground processing of aircraft
9	105	En route weather
10	133	ATC delay
11	144	MOG
12	202	Crew rest
13	913	Landing gear
14	124	Base operation
15	127	POL
16	134	NON receipt of diplomatic clearance
17	142	Down line station restriction(AMC)
18	143	Down line station restriction(NAF)
19	163	other

Table 3.15 The Top 19 Airlift Delay Codes Identified by DR



(a) (b)

Figure 3.14 (a) ADT Mission Type Pareto Chart (b) Airlift Average Delay Time Against Delay Codes

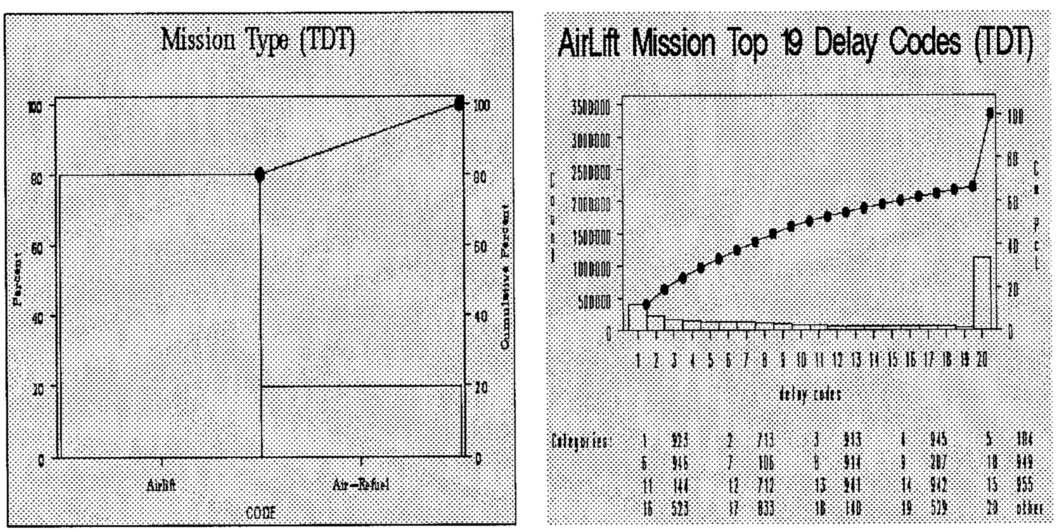
way the Pareto chart identified the vital few delay codes for airlift mission. The measurement characteristic here is the ADT for each delay code over a 13 month period. Table 3.16 lists the corresponding delay codes over 13 month period. Here, however, the top 19 delay codes, account for only 40% of the total, leading to few obvious conclusions.

3.4.3 Results Using Total Delay Time as an MOE. Finally, the author took TDT on this pivot. Figure 3.15, part (a) shows that airlift missions still dominate. Figure 3.15, part (b) displays a Pareto chart for the vital few delay codes, while Table 3.17 explains what the delay codes means. Here it becomes clear that mechanical problems contribute most to the delay time experienced.

3.4.4 Further Analyses by Mission Type. The three MOEs each identified airlift missions as the most important, which shows again that they all have similar ability to identify where the opportunities for improvement may be.

Mission	Delay Codes Identified by Average Delay Time	
Rank	**Delay Code**	**Description**
1	970	unknown
2	555	Deviation unresolved
3	126	Supply
4	716	Order and ship time exceed
5	717	Supply issued wrong part
6	964	intercom
7	991	emergency
8	192	Awaiting medical equipment to accompany patient in flight
9	713	Stock level maintain, but the item is not listed
10	799	Other logistics Supply
11	712	Stock Levels not maintain for this aircraft
12	833	Saturation ot Shortage of supply equipment
13	271	Awaiting diplomatic clearance for unit plan mission
14	524	Deviation directed to match home station crew
15	182	Awaiting medical equipment
16	523	Deviation directed ot support higher priority mission
17	955	MADARS
18	500	Unknown
19	210	Crew availability

Table 3.16 The Top 19 Airlift Delay Codes Identified by Average Delay Time



(a) (b)

Figure 3.15 (a) TDT Mission Type Pareto Chart (b) Airlift Pareto Charts on Total Delay Time Against Delay Codes

	Delay Codes Identified by Total Delay Time	
Rank	Delay Code	Description
1	923	Power plant
2	713	Stock level maintain, but the item is not listed
3	913	Landing gear
4	945	Hydraulic and pneumatic power supply
5	104	Preluded takeoff
6	946	Fuel system
7	106	Arrival station weather precluded a safe landing
8	914	Flight control
9	207	Crew duty time insufficient
10	949	Misc Utility
11	144	Down line station MOG
12	712	Stock Levels not maintain for this aircraft
13	941	Air conditioning
14	942	Electronic power supply
15	955	MADARS
16	523	Deviation directed ot support higher priority mission
17	833	Saturation ot shortage of supply equipment
18	140	Departure station restriction
19	529	Other management deviations

Table 3.17 The Top 19 Airlift Delay Codes Identified by Total Delay Time

order	Category	Accountable Agency	DR	ADT	TDT
1	Weather	AMC(DO)	4	0	2
2	Events and Incidents	AMC(SP), NAF, AMC(DO)	0	0	0
3	Host Base Support(at AMC bases)	NAF	1	0	0
4	Host Base Support(at Non-AMC bases)	AMC(SV,LG,DO)	1	1	0
5	External Agencies	AMC(DO)	2	0	0
6	Airfield	AMC(DO), NAF	5	0	2
7	Contract Carrier Controllable	AMC(DO)	1	0	0
8	User	AMC(DO)	0	0	0
9	Aeromedical Evacuation (Medical Support (Non-AMC)	AMC(SG)	0	2	0
10	Aeromedical Evacuation (Medical Support AMC	NAF	0	0	0
11	Aircrew	AMC(DO), NAF	1	1	1
12	Management and Coordination	NAF	0	0	0
13	Unit Planning	NAF	0	1	0
14	Other	AMC(DO)	0	0	0
15	Management	NAF	0	0	0
16	Passenger Service	NAF	0	0	0
17	Air Freight	NAF	0	0	0
18	Fleet Service	NAF, AMC(DO)	0	0	0
19	Execution	TACC	1	0	0
20	Planning	TACC	0	0	0
21	Management	TACC	1	3	2
22	Logistics Deviation Indicators Supply	AMC(LG), NAF	0	5	2
23	Logistics Deviation Indicators Saturation ot shortage	NAF, AMC(LG)	0	0	1
24	Airframe	NAF	1	0	2
25	Power Plant	NAF	1	0	1
26	System	NAF	0	3	6
27	other	NAF	0	0	0
28	unknown		0	2	0

Table 3.18 The Comparison of Accountable Delay Category Between DR, ADT and TDT for the Airlift Mission

Order		DR		ADT		TDT	
	Accountable Agencies	frequency	Percentage	frequency	Percentage	frequency	Percentage
1	AMC(DO)	12	.632	0	0	4	.210
2	AMC(LG)	0	.053	5	.263	2	.105
3	AMC(SG)	0	0	1	.053	0	0
4	AMC(SP)	0	0	0	0	0	0
5	AMC(SV)	0	0	0	0	0	0
6	NAF	4	.210	8	.421	11	.579
7	TACC	2	.104	3	.158	2	.105
8	Unknown	0	0	2	.105	0	0

Table 3.19 The Comparison of Accountable Agencies Between DR, ADT and TDT for the Airlift Mission

Meanwhile, a comparison of results is summarized in Tables 3.18. Basically, the phenomena observed in the previous two sections still can be seen here. DR and TDT share 5 delay codes (code 923, 104, 106, 144, and 140), TDT and ADT share 3 delay codes (code 712, 955, and 833), and DR and ADT does not share any delay code. Hence, three MOE dose not share any common delay code. In this case, TDT can be treated as a compromise of DR and ADT.

Table 3.19 summarized the results for "accountable agencies" DR and TDT focus on some specific accountable agencies. ADT tends to identify "AMC(LG)" and has different perspective from the other two MOEs.

3.5 Comparative Pareto Charts

The author realized that trend charts have their defects when observing the performance of various subgroups over time process because when the plotted points are close to each other or cross over each other, there is no easy way to discern which subgroup is better or which is worse. The author thus adapted the original Pareto chart concept to monitor the particular measurement characteristic over time.

The author picked number of DR and ADT as the MOE and "CvsMil" as the pivot to demonstrate the use of the comparative Pareto charts. These are shown in Figure 3.16 and 3.17. The measurement characteristics here are the monthly number of delays and ADT for each type of aircraft from June 95 to May 96. The rank order is based upon the performance in the first month. For instance, in Figure 3.17 part

(a), the C-5 subgroup had the highest ADT and the C-17 subgroup had the lowest. The rest of the charts follow this ranking.

Part (a) in Figure 3.16 and 3.17 described the number of delays and ADT for each type of aircraft in June and July 95. Likewise, part (b) represents each subgroup's performance in August and September 95', and so on. Basically, the comparative Pareto chart has a similar function to the trend chart in Figure 3.4 and, as we can see, some subgroup perform very similar, like the KC-10 and KC-135. A better sense of rank can still get it from a Pareto chart's perspective.

The reason that the author presented this idea is because the trend chart is one of the current techniques the MRO is using to monitor and improve DR. The comparative Pareto chart provides another alternative that is easier to discern and interpret.

3.6 Discussion About the Difference Among DR, TDT, ADT

Based on the thorough Pareto chart analysis conducted in this chapter, several phenomena can be observed.

First, it is not hard to notice that the vital few delay codes identified by the DR are similar to the ones identified by TDT. Actually, both tend to identify the maintenance type of delay codes as "Accountable delay categories" and "AMC(DO)" and "NAF" as "accountable agencies." The reason for this might be that TDT implicitly accounts for the number of associated delays. In other words, the higher the number of occurrences, the bigger the TDT. That's why they are related to each other.

Secondly, compared to the DR, the "other" bar in each TDT Pareto chart is less than the one in the corresponding Pareto charts based on the other two MOEs. This means that the vital few from the TDT Pareto charts are easier to identify. However, in most cases, the Pareto analysis did not expose a small number of obviously important delay codes as generally expected with such analyses. The

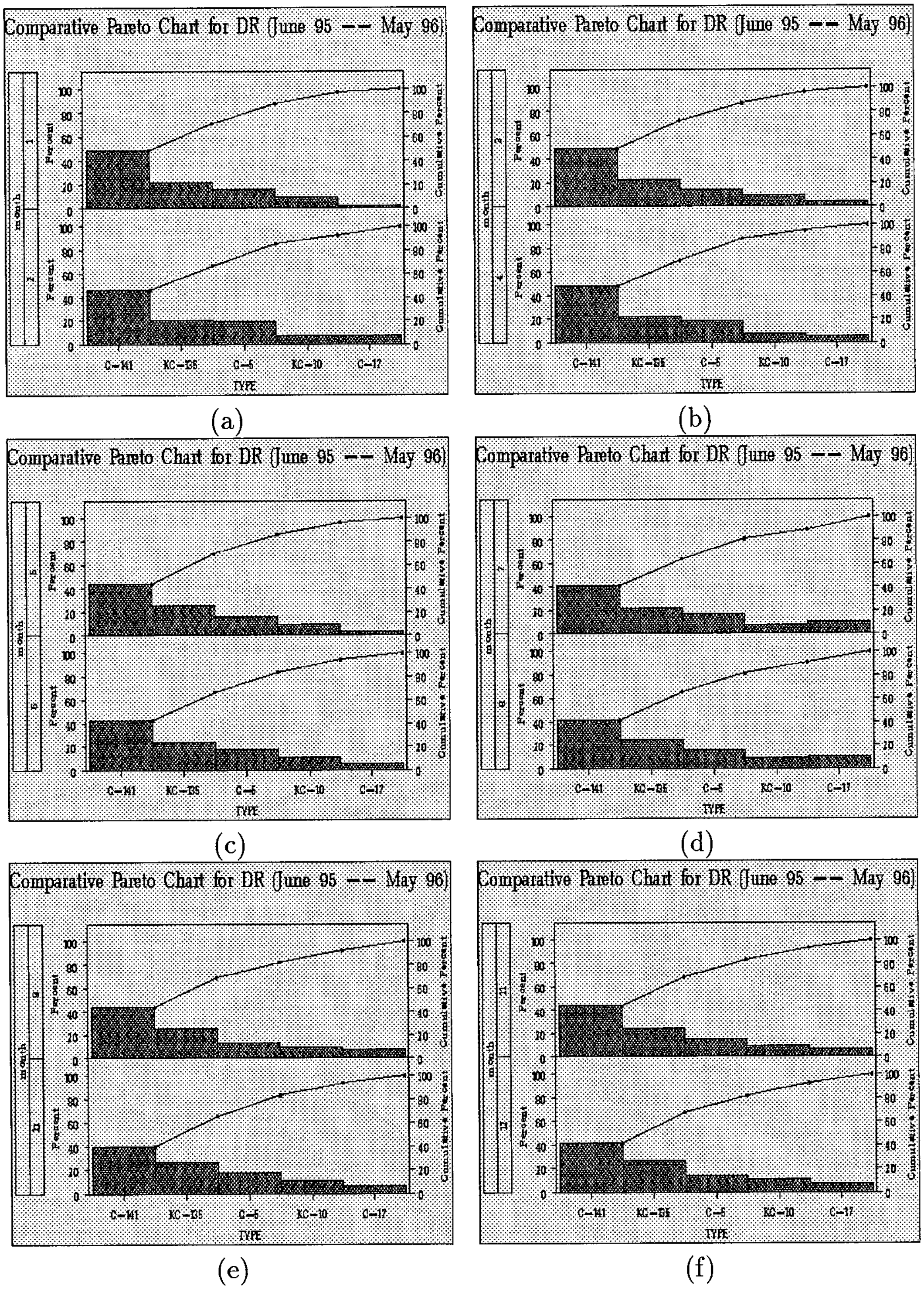
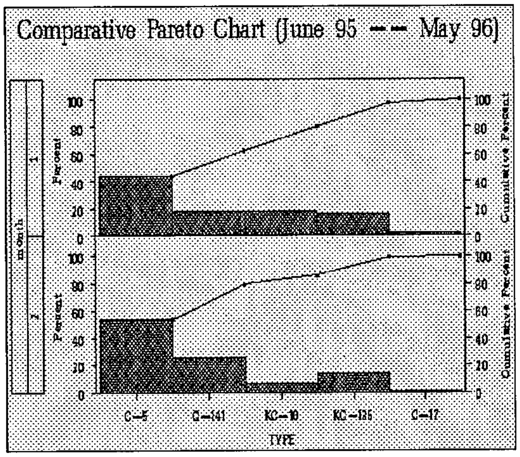
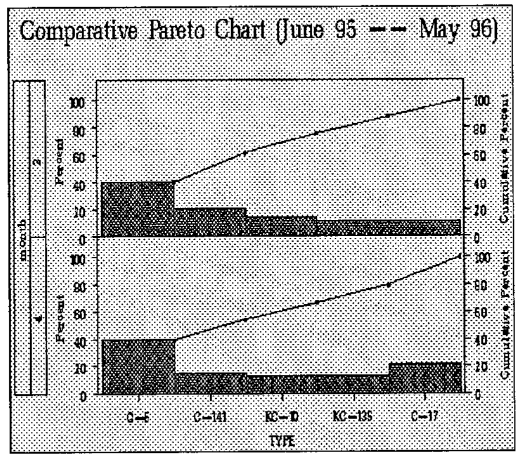


Figure 3.16 Comparative Pareto Charts to monitor Over Time CvsMIl on DR : (a)1=Jun 95, 2=Jul 95, (b)3=Aug 95, 4=Nov 95 (c)5=Oct 95, 6=Nov 95, (d) 7=Dec 95, 8=Jan 96 (e) 9=Feb 96,10=Mar 96, (f) 11=Apr 96, 12=May 96



(a)



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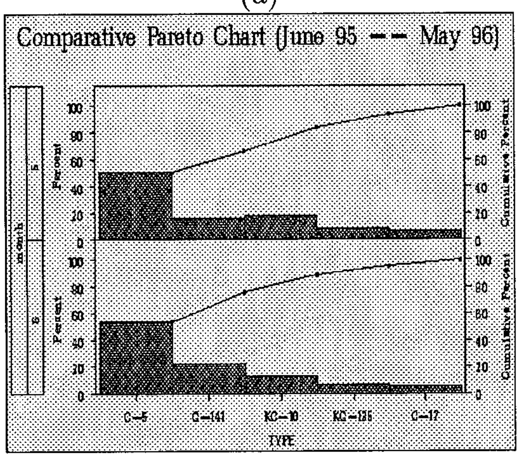

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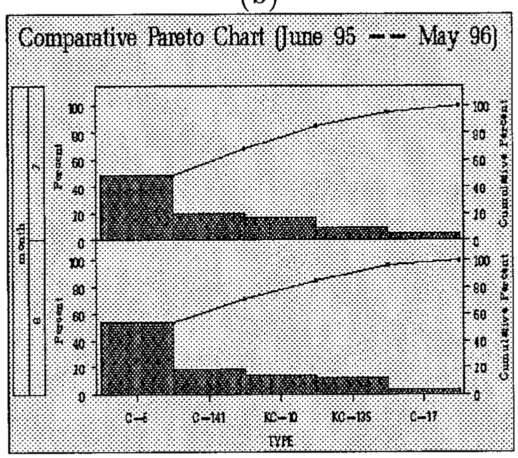

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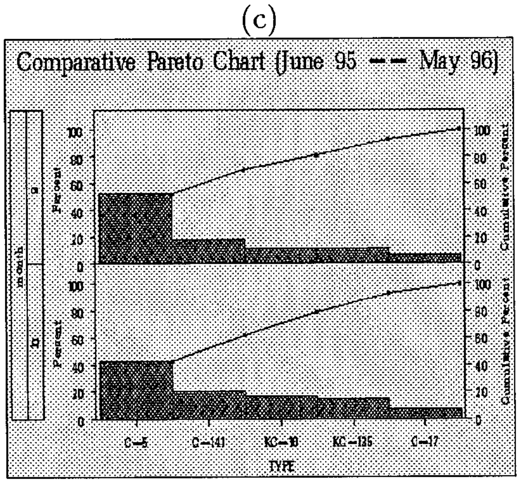
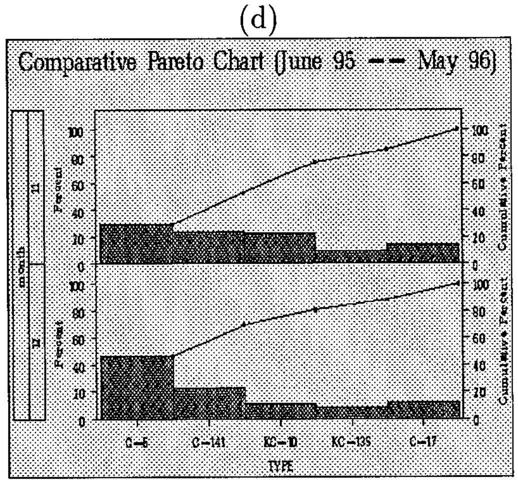


(e)



(f)

Figure 3.17 Comparative Pareto Charts to monitor Over Time CvsMIl on ADT : (a)1=Jun 95, 2=Jul 95, (b)3=Aug 95, 4=Nov 95 (c)5=Oct 95, 6=Nov 95, (d) 7=Dec 95, 8=Jan 96 (e) 9=Feb 96,10=Mar 96, (f) 11=Apr 96, 12=May 96

Delay Codes	DR			ADT			TDT		
	Before	**After**	**IP**	**Before**	**After**	**IP**	**Before**	**After**	**IP**
923	69%	73%	4%	261.5	232.5	10.4%	3605109	3204099	11.1%
555	69%	69%	0%	261.5	260.5	0.4%	3605109	3590602	0.4%

Table 3.20 Improvement After Taking out of the Number One Delay Code for 3 MOEs

author concluded that the DR improvement process is very complex and that delays result from a large number of relatively insignificant causes. In AMC's terminology, there are few if any obvious "low hanging fruit" ripe for picking.

Thirdly, the vital few identified using ADT as the MOE have a completely different perspective from the other two. The author assumes this somehow gives a fair consideration of all perspectives, but concludes that ADT is less informative as a MOE. The author set the C-5 aircraft as an example. In this subgroup, both DR and TDT identify delay code 923 as the number one vital few, ADT identifies delay code 555. Delay code 923 occurred 512 times or caused 401010 minutes delay over the 13 month period. Delay code 555 happened twice or caused 14507 minutes delay. The author then took out the related delay departures with these two delay codes and recalculated the performance for three different MOEs. In other words, these delayed departures are considered as on-time departures now. The improvement results are summarized in Table 3.20. The author use the "IP" to stand for the improvement percentage.

Based on Table 3.20, the delay code 555 can not improve the performance even though it is identified by ADT as the top one Vital few. However, the delay code 923 improves DR by 4%, ADT by 10% and TDT by 11%. This result verifies the conclusion above that ADT is less informative in the context of identifying the greatest opportunity for improvement. However, this might suggests that logistics type of problems cause extreme long delays. Improvement from the supply chain of component might be a necessary.

Based on all the results in this chapter, from a perspective of the "delay code categories," "logistics deviation Indicator supply" or "system" category is the most identified category. From an "accountable agencies" perspective, AMC(DO), AMC(LG) and NAF are assumed to share the responsibility.

One more thing worth mentioning is that the each vital few delay code can be treated as a quality characteristics. The accountable agencies could use the cause and effect diagram mentioned in Chapter 2 to figure out where things goes wrong.

3.7 Further Statistical Analysis

In Section 3.2, some of the DR for each type of aircraft are similar. For instance, DR was 81% for the C-141, and 83% for the KC-135. It is interesting to know whether or not this implies a statistically significant difference in performance among the five aircraft. In Section 3.3, it was seen that the DR for the two numbered air forces were similar, specifically DR was 78% for the 21st NAF and 83% for the 15th NAF. Likewise, an important question is whether or not this indicates a statistically significant difference in performance between the two NAFs. Indeed, similar questions can be asked in relation to the relative performance between all the other subgroups examined in this chapter. In this section, the making of such comparisons using more formal statistical methods is demonstrated. These examples can be extended in an obvious manner to cases beyond those demonstrated.

3.7.1 Confidence Intervals on Proportions. Recalling that DR is the proportion of on-time departures, the objective is to develop an interval estimate of the DR that can be expected for a particular subgroup in the long run, assuming that the departure process continues to operate as it has in the past. In order to do this, we assume that every departure within a subgroup has the same probability, p, of being on time; if true, this probability represents the departure reliability expected for this subgroup and an interval estimate of p can be constructed using standard statistical results for confidence intervals on proportions.

In particular, if $\hat{p}$ represents the departure reliability experienced within a set of n departures, then a $100(1-\alpha)\%$ confidence interval (CI) on $\hat{p}$ is given by

$$\hat{p} \pm Z_{\alpha/2}\sqrt{\hat{p}(1-\hat{p})/n} \tag{3.1}$$

In this formula, it is assumed that the sample size n is large enough to assume that the normal approximation to the binomial distribution applies ((28):358). We refer to this as a $100(1-\alpha)\%$ confidence interval on p since, under the assumptions we have made, the probability that this interval contains the proportion of delays, p, that will be experienced in the long run is $100(1-\alpha)\%$.

Based on the data contain in Table 3.1, a 95% CI on DR for each type of aircraft is calculated as follows.

$$\text{The C-5 aircraft} \Rightarrow 0.6946 \pm 1.96\sqrt{.6946 * .3054/13783}$$
$$\text{The C-17 aircraft} \Rightarrow 0.8840 \pm 1.96\sqrt{.8840 * .1160/5300}$$
$$\text{The C-141 aircraft} \Rightarrow 0.8058 \pm 1.96\sqrt{.8058 * .1942/37081}$$
$$\text{The KC-10 aircraft} \Rightarrow 0.8466 \pm 1.96\sqrt{.8466 * .1533/8066}$$
$$\text{The KC-135 aircraft} \Rightarrow 0.8304 \pm 1.96\sqrt{.8304 * .1696/20180}$$

or equivalently,

$$\text{The C-5 aircraft} \Rightarrow .6869 < E(DR_{theC-5}) < .7023$$
$$\text{The C-17 aircraft} \Rightarrow .8763 < E(DR_{theC-17}) < .8917$$
$$\text{The C-141 aircraft} \Rightarrow .7981 < E(DR_{theC-141}) < .8135$$
$$\text{The KC-10 aircraft} \Rightarrow .8389 < E(DR_{theKC-10}) < .8543$$
$$\text{The KC-135 aircraft} \Rightarrow .8252 < E(DR_{theKC-135}) < .8355$$

since the preceding five confidence intervals do not overlap, we can conclude that there is a statistical significant difference in the expected departure reliability for the 5 types of aircraft.

As to NAF, based on the data contained in Table 3.10, a 95% CI on DR for the 21st NAF is thus given

$$0.7835 \pm 1.96\sqrt{.7835 * .2165/47412}$$

or equivalently

$$.7797 < E(DR_{21stNAF}) < .7872$$

indicates that the 78% point estimate of DR for this NAF is accurate to the roughly nearest one percent. Similarly, a 95% CI on DR for the 15th NAF is given by

$$.8262 \pm 1.96\sqrt{.8262 * .1738/36781}$$

or equivalently

$$.8224 < E(DR_{15thNAF}) < .8301$$

Since the preceding two confidence intervals do not overlap, we can further conclude that there is a statistically significant difference in the expected departure reliabilities for the two numbered air forces.

Finally, for completeness, note that a 95% CI for the UK NAF turns out to be

$$.7334 < E(DR_{UKNAF}) < .8413$$

This interval is much wider than the preceding intervals because only 221 departures have been recorded for this NAF, as compared to 47,412 and 36,781 departures, respectively, for the 21st and 15th NAFs. With a width of nearly 0.11, this interval indicates that the point estimate of DR for the UK NAF displayed in Table 3.8, 0.79, is roughly accurate to the nearest 0.05. Since this last CI overlaps the preceding two CIs, it can not be concluded that the expected DR for the UK NAF is significantly different from those for either the 21st ot 15th NAFs.

3.7.2 Confidence Interval on the Difference Between Two Proportions. Confidence Interval on the Difference Between Two Proportions. In the preceding section, the fact that the CIs on DR for the 21st and 15th NAF did not overlap formed the basis for concluding that the expected DRs were significantly different. This comparison also could be made more directly, and with more precision in general, by constructing a $100(1-(\alpha))\%$ confidence interval on the difference between two proportions. In order to do this, we assume that every departure within the first subgroup has the same probability, p1, of being on time while that every departure within the second subgroup has the same probability, p2, of being on time. Then, if $\hat{p1}$ and $\hat{p2}$ represent the departure reliabilities experienced within a set of n1 departures within the first subgroup and within a set of n2 departures within the second subgroup, respectively, then a $100(1-(\alpha))\%$ confidence interval (CI) on $p1 - p2$, is given by

$$\hat{p_1} - \hat{p_2} \pm Z_{\alpha/2}\sqrt{\frac{\hat{p_1}(1-\hat{p_1})}{n_1} + \frac{\hat{p_2}(1-\hat{p_2})}{n_2}} \tag{3.2}$$

In this formula, it is assumed that the sample sizes are large enough to assume that that the normal approximation to the binomial distribution applies ((28):358).

For example, a 95% CI on the difference in the expected DRs of the 21st and 15th NAFs is given by

$$.7854 - .8262 \pm Z_{\alpha/2}\sqrt{\frac{.7854 * .2165}{47412} + \frac{.8262 * .1738}{36781}}$$

or

$$-0.0482 < E(DR_{21thNAF} - DR_{15thNAF}) < -0.0374$$

Since this CI does not include zero, this confirms the earlier conclusion that there is indeed a significant difference in the expected DRs for these two numbered air forces. On the other hand, the two other comparative CIs that can be constructed are

$$-0.0580 < E(DR_{21thNAF} - DR_{UKNAF}) < 0.0502$$

$$-0.01520 < E(DR_{15thNAF} - DR_{UKNAF}) < 0.0930$$

which indicate, as concluded before, that there is no statistically significant difference between the expected DR for the UK NAF and either of those for the 21st ot 15th NAFs.

IV. Control Charts

The purpose of this chapter is to demonstrate how control charts can be used to monitor DR performance. A control chart is a technique used to tell if the observations made on a process exhibit behavior consistent with that of an "in control" process. Control charts are, perhaps, the most commonly used of all SPC tools. There are different kinds of control charts for different needs, distinguished by the sample statistic being monitored. Table 4.1 lists some classic control charts, which are also called Shewhart control charts.

The purpose of a control chart is to determine whether or not a process is operating in a state of statistical control, i.e., whether or not the observed variability is due solely to chance cause variation. In general, control charts are used to identify fundamental changes in the process (as manifested by the occurrence of assignable causes). Behavior that is not consistent with chance cause variation alone is evidence for the presence of assignable causes; these then need to be detected, identified and eliminated. In order to demonstrate control charts use in terms of AMC's case, the author chose to apply them overall performance. They can be applied in more specific contexts as described.

From a statistical perspective, control charts are equivalent to perform a series of hypothesis tests over time. This technique monitors monthly observation in the process if it is statistical equal to the process mean and use the chart to show how far the observations are away from the process mean.

	Type of Chart	**Description**
1	M	Sample Median
2	P	Proportion of Conforming
3	S	Sample Standard Deviation
4	$\overline{X}$	Sample Mean
5	R	Sample Range

Table 4.1 Possible Control Charts on AMC's Database

From a SPC's aspect, the observation above the UCL is considered as "out of control." However, in AMC's case, when proportion type of MOE is considered as measurement characteristic, observation falling above the UCL stands for a surprising good DR result. Consequently, when the DR is the MOE, it is important to notice that the UCL is useless in this context. The observations above the UCL is actually "out of control" in a good way. Only the observations which are below the LCL is the real "out of control" signal. There is no this kind of difference when the MOE is ADT.

In AMC's situation, the general model assumed for a control chart is that, when the departure process is in control, delays occur as the result of many different chance causes, each of which has a relatively small impact on overall performance. However, when the departure process is out of control, behavior is different. The MOE (or test statistic) being monitored (for example, the proportion of on time departures or the average delay time) takes on a value that is unlikely to have occurred due to chance cause variation alone. This signals that the process might be out of control. From a statistical perspective, an out of control signal occurs when the MOE being plotted takes an a value that is statistically significant from its in-control mean.

One thing that is worth mentioning is that the objective of control charting is not to improve the process but rather to ensure that the process continues to operate in the in-control state. It is also important to note that this has nothing to do with goals or specifications for the processes. Besides traditional control charts, the author applied charts developed for dealing with small shifts and auto-correlated data, such as exponentially weighted moving average (EWMA) (15). Two difference MOEs, DR and ADT, will be examined in this chapter.

4.1 Principal of Control Charts

Control charts are defined as follows:

Control charts are a graphical display of a quality characteristic that has been measured or computed from a sample versus the sample number or time. The chart contains a center line that represents the average value of the quality characteristic corresponding to in control state. Two other horizontal lines, called the upper control limit (UCL) and the lower control limit (LCL), are also shown in the chart ((18):103).

Thus, the general mathematical model for the control charts is:

$$\begin{aligned} UCL &= \mu + k * \sigma \\ \text{Center Line} &= \mu \\ LCL &= \mu - k * \sigma \end{aligned}$$

where k is the distance of the control limit from the center line, and μ and σ are respectively, the mean and standard deviation of the statistics being monitored when the process is in control. Traditionally, k is assigned to be 3. The resulting chart is of the referred to as a Shewhart Control chart. Figure 4.1 depicts a typical control chart. Roughly, whether the process is "in control" or "out of control" can be decided by where the observations fall. If they are within the control limits, this process is assumed to be "in control" and if the process are outside the control limits, the process is assumed to be out of control. Actually, there are some additional rules called "sensitizing rules" for control charts to discern if processes are out of control even though the observations are within these two limits. These rules are set up to increase the sensitivity of the control charts by identifying patterns that would be very unlikely to occur if the process was indeed in control ((18):117).

To AMC, a conclusion of an "in control process" would mean that the variation around the process mean is acceptable, while an "out of control" conclusion would mean otherwise. The latter is likely a sign to indicate that some assignable cause has occurred and needs to be corrected.

Control charts have a lot of advantages over the other quality improvement

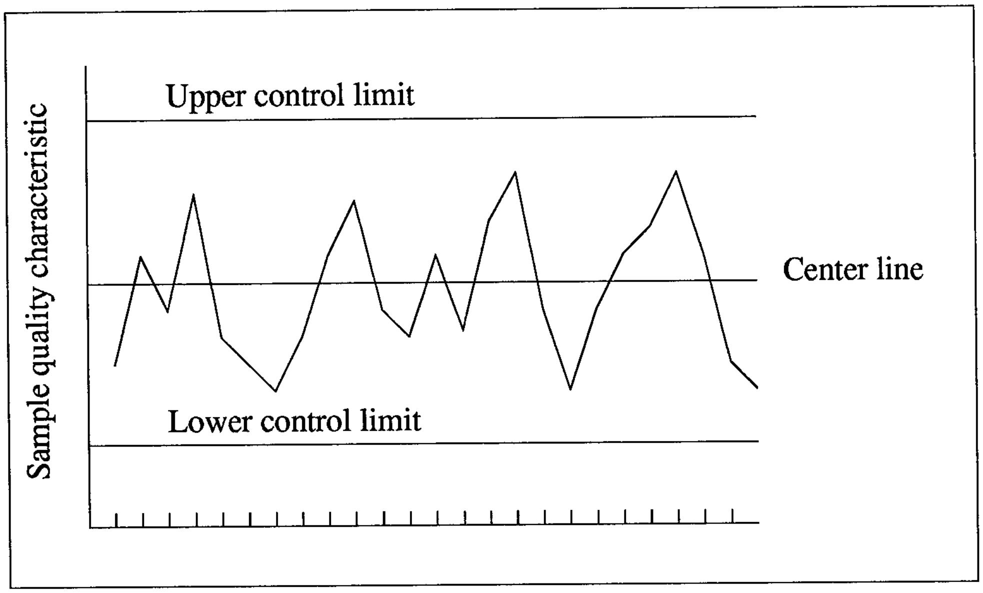


Figure 4.1 A Typical Control Chart

processes. Some of these are enumerated in ((18):112).

Control charts can be divided into attribute-type charts like P-Chart[1] for variables that are based on counts, such as proportion, and variables-type charts that are based on continuous measurements. This thesis will conduct the analysis of the application of attribute-type charts to departure reliability and will try to find a suitable, alternative variables-type of MOEs to assess on-time performance.

4.2 Control Charts for DR

Because DR is a proportion type of MOE, it is typically monitored with a P chart. This type of chart is constructed by assuming that when the process in control, the proportion of on-time departures is some value p; ie, we assume, as a working model, that the probability of delay on any given departure is $1-p$. Then, number of on-time departures observed within n departures has a binomial distribution with mean np and variance $np(1-p)$. It follows that the the proportion of delays observed

[1]Proportion

within n departures is a random variable with mean np and variance $np(1-p)/n$. The typical representation of P chart is as follows.

$$\begin{aligned}
\text{LCL} &= p - 3 * \sqrt{\frac{p*(1-p)}{n}} && (4.1)\\
\text{CL} &= p && (4.2)\\
\text{UCL} &= p + 3 * \sqrt{\frac{p*(1-p)}{n}} && (4.3)\\
& && (4.4)
\end{aligned}$$

Unfortunately, there are two potential problems that hinder this model in AMC's situation. First of all, the true value of p is not known. One reasonable approach is to estimate it from the data. In AMC's case, p can be estimated, with overall proportion of delays over the 13-month period. Since this is equal to 0.802, then

$$\begin{aligned}
\text{LCL} &= 0.802 - 3 * \sqrt{\tfrac{0.802(1-0.802)}{n_i}}\\
\text{Center line} &= 0.802\\
\text{UCL} &= 0.802 + 3 * \sqrt{\tfrac{0.802(1-0.802)}{n_i}}
\end{aligned}$$

where n_i is the number of departures that occur in the time period (month) observed. Second of all, AMC's monthly numbers of missions are different from each other. That is, n changes from month to month. This will cause the control limits to vary with the sample size, making it hard to interpret patterns. Generally speaking, there are 3 approaches for overcoming this varying sample size. These are to simply use the varying limits; to develop a chart with limits based on average sample size; and to use a standardized control chart. The author will demonstrate each by using the dataset of overall AMC performance. Table 4.2 shows this database. The last column are the standardized values used within standardized control charts, which will be explained in a while.

Case	Month	Number of Missions	Number of on-time Departures	DR	Z
1	Jun 95	6028	4868	0.808	1.169
2	Jul 95	6459	5048	0.782	-4.033
3	Aug 95	6909	5649	0.818	3.337
4	Sep 95	5854	4642	0.793	-1.728
5	Oct 95	6809	5463	0.802	0
6	Nov 95	5747	4527	0.788	-2.663
7	Dec 95	6668	4989	0.748	-11.065
8	Jan 96	6552	4934	0.753	-9.953
9	Feb 96	6662	5142	0.772	-6.144
10	Mar 96	7023	5739	0.817	3.154
11	Apr 96	7037	5894	0.838	7.57
12	May 96	6641	5715	0.861	12.065
13	Jun 96	6025	5099	0.846	8.570

Table 4.2 Monthly Overall Performance Dataset (DR)

4.2.1 P Chart with Varying Limits. Since the sample size of the monthly subgroups are different, "n" in Equation 4.4 is replaced with n_i. Hence, the model for this is

$$UCL = \overline{p} + 3 * \sqrt{\frac{\overline{p}(1-\overline{p})}{n_i}} \tag{4.5}$$

$$\text{Center Line} = \overline{p} \tag{4.6}$$

$$LCL = \overline{p} - 3 * \sqrt{\frac{\overline{p}(1-\overline{p})}{n_i}} \tag{4.7}$$

$$\tag{4.8}$$

where $\overline{p} = 0.802$. This chart will have a constant center line but varying control limits. For in Jun 95, the number of missions was 6028, hence,

$$\begin{aligned} UCL &= 0.802 + 3 * \sqrt{\frac{0.802(1-0.802)}{6028}} \doteq .8173 \\ CenterLine &= 0.802 \\ LCL &= 0.802 - 3 * \sqrt{\frac{0.802(1-0.802)}{6028}} \doteq .7866 \end{aligned}$$

while in July 95, the number of mission was 6459, so that

$$\begin{aligned} UCL &= 0.802 + 3 * \sqrt{\frac{0.802(1-0.802)}{6459}} \doteq .8169 \\ CenterLine &= 0.802 \end{aligned}$$

$$LCL = 0.802 - 3 * \sqrt{\frac{0.802(1-0.802)}{6459}} \doteq .7871$$

The P Chart with varying limits for the overall performance is shown in Figure 4.2, part (a). It is easy to see that AMC's overall performance was clearly out of control during Dec 95 to Feb 96 period. This behavior is discussed after examing the other types of charts.

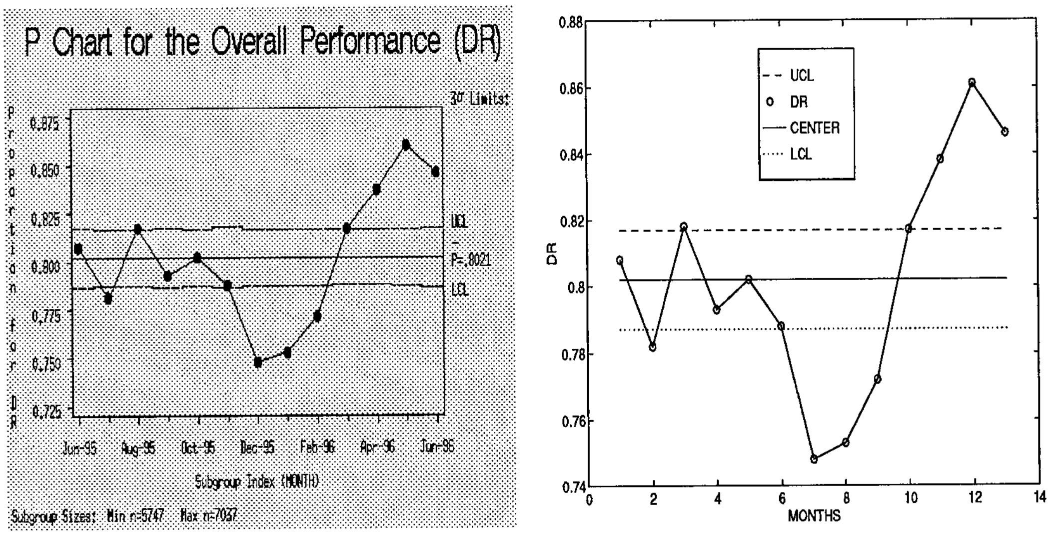
4.2.2 P Chart with Limits Based on Average Sample Size. From Figure 4.2 (a), it is clear that although the control limits varying from month to month, they do not differ substantially. This suggests that an alternative approach would be to develop control limits based on an average sample size, $\overline{n}$ ((18):185). This is calculated simply

$$\overline{n} = \sum_{i=1}^{m} \frac{n_i}{m} \tag{4.9}$$

where "m" is the number of months observed. In this context, of course, $m = 13$ and the average sample size turns out to be $84414/13 \doteq 6493$. Thus, a P-chart with limits based on this average sample size has the form

$$\begin{aligned} UCL &= 0.802 + 3 * \sqrt{\frac{0.802(1-0.802)}{6493}} \doteq .8168 \\ \text{Center Line} &= .802 \\ LCL &= 0.802 - 3 * \sqrt{\frac{0.802(1-0.802)}{6493}} \doteq .7871 \end{aligned}$$

The P Chart based on average sample size for the overall performance is shown in Figure 4.2, part (b). This figure shows that AMC's performance is not stable at all, and out of control most of the time.



(a) (b)

Figure 4.2 Overall P Chart with (a) Varying Limits (b) Based on Average Sample Size

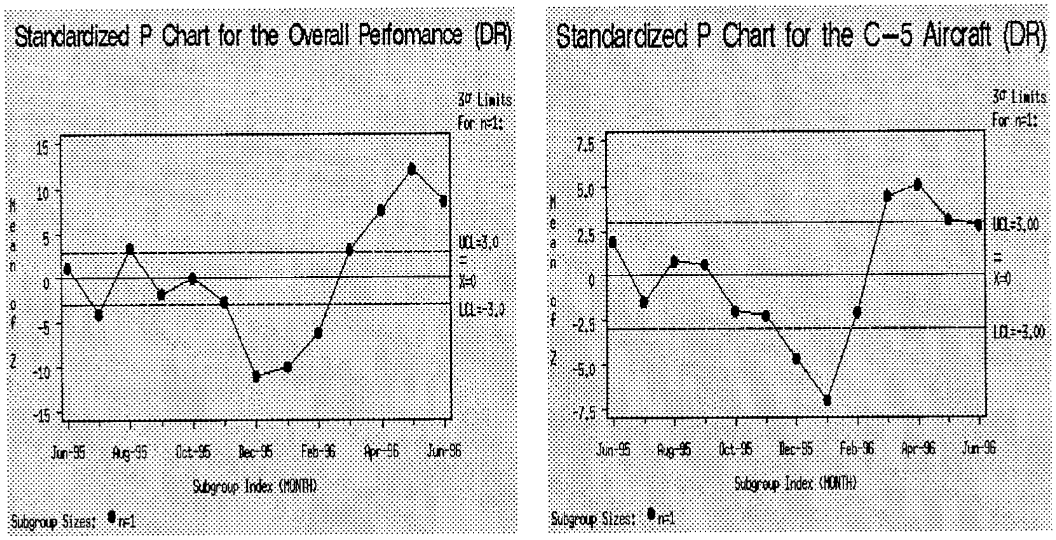
4.2.3 Standardized P Chart. This approach converts all the plotted points into standard deviation units. Montgomery ((18):167) states that the control chart has the center line at 0 and upper and lower control limits of ±3. The variable plotted on the chart is

$$Z_i = \frac{p_i - p}{\sqrt{p(1-p)/n_i}} \tag{4.10}$$

where p_i is the monthly observation. In Jun 1995, DR was 0.808, so that

$$Z_i = \frac{0.808 - 0.802}{\sqrt{0.802(1-0.802)/6028}} \doteq 1.169$$

The standardized P chart for the overall performance is shown in Figure 5.1, part(a) shows that AMC's performance was out of control during Dec 95 to Feb 96, part (b) for the C-5 aircraft subgroup, its performance was similarly out of control around Dec 95 to Feb 96 period.



(a) (b)

Figure 4.3 Standardized P Chart (a) Overall Performance (b) The C-5 Aircraft

4.2.4 The Pros and Cons of Three P Chart Approaches. There are pros and cons for these 3 different approaches of dealing with various sample size of subgroups. The first approach is to apply a P-chart with varying limits. The width of the control limits is inversely proportional to square root of the sample size ((18):163). In other words, the bigger the size of samples, the narrower the width of control limits. The disadvantage of this approach is that control limits are not constant and thus, patterns in the plotted points may be hard to detect.

The second approach is to use a P-chart with limits based on average sample size. This approach treats the unequal sample size as equal sample size, and assumes that future sample size will not differ greatly from the previous sample size. Montgomery ((18):165) states that if this approaches is used, the resulting control chart will not look as formidable to operating personnel as the control chart with variable limits.

The last approach is to use a Standardized P-chart. Montgomery states that if there is large variation in sample size, then run rules and pattern-recognition methods can only be safely applied to the standardized control chart. However, the

disadvantage of this type of control chart is that the statistic plotted is measured in standardized units and thus loses the original context of the original measurements. Montgomery ((18):167) suggests maintaining a control chart with individual control limits for each sample to provide process context for the operating personnel, while simultaneously maintaining a standardized control chart for the quality engineer's use.

4.2.5 Interpretation of Results. Each of the three types of P-charts exhibits the same basic behavior for the overall, monthly DR. In fact, for the sample sizes observed, there is little practical difference between the three. Indeed, although the sample sizes do vary from month to month, the control limits for the chart that uses these explicitly do not differ radically from the control limits based on average sample size, and the same basic pattern is observed in the standardized chart.

What is surprising is that the charts all strongly suggest that the departure process is out of control. That is, it does not appear that delays occur from month to month according to a constant system of chance causes. Or, in other words, in relation to the assumed model that the number of delays per month follows a binomial distribution with the same probability of delay each month, the variation exhibited from month to month is statistically significant. (If only chance causes were at work according to the assumed model, than the vast majority of observations should fall within the control limits.) Most vivid is the evidence of a significant and increasing trend in DR over 6 of the last 7 months observed.

This apparent trend might provide AMC analysts with additional clues for identifying opportunities for process improvement if they could identify any changes in Command behavior or operating policy that took place over that 7-month period. On the other hand, this could also reflect the fact that the departure process has been under tremendous Commander-level observation and scrutiny, leading to implicit changes in human performance or under-reporting of delays. (This latter

phenomenon is known in the industrial engineering literature as the "Hawthorne effort.")

4.3 Control Charts for ADT

Delay times are variables type of measurements and it is customary to monitor such variables using $\overline{X}$ charts (to monitor the mean) and S or R charts (to monitor the standar deviation.) Further, an $\overline{X}$ chart is a control chart in which the statistic being monitored is the average of a sample of variables-type measurements taken from the process. In doing so, it is assumed that, when the departure process is in control, the delay time associated with a departure is a random variable with mean μ_0 and standard deviation σ_0. Then, as a result, the average delay experienced within a set of n departures is a random variable with mean μ_0 and standard deviation $\sigma_0/\sqrt{n}$.

Just like what happened in P-charts, the true values of μ_0 and σ_0 are unknown. Likewise, are could either assume values for these or estimate them from the data; the latter makes the most sense because it is not necessarily know what their values theoretically should be when the process is in control. The author will estimate the values of μ_0 and σ_0 for the overall performance dataset over the 13-month period as a demonstration. Table 4.3 lists this dataset. The average delay time per month are shown in the 5th column in Table 4.3, the standard deviations of these delays, by month, are shown in the 6th column and the standardized values are in the 7th column.

Montgomery ((18):230) states

> Generally, $\overline{x}$ and S charts are preferable to their more similar counter parts, $\overline{x}$ and R charts, when either
>
> 1. The sample size n is moderately large, say $n \geq 10$ or 12 (recall that the range methods for estimating σ loses statistical efficiency for moderate to large samples.)
> 2. The sample size n is variable.

Case	Month	Number of Missions	Number of on-time Departures	ADT	S.D.	Z
1	Jun 95	6028	4868	116.11	391.67	-0.1392
2	Jul 95	6459	5048	142.77	761.93	3.5981
3	Aug 95	6909	5649	97.87	107.50	-2.7991
4	Sep 95	5854	4642	117.37	553.06	0.0312
5	Oct 95	6809	5463	128.79	674.15	1.6792
6	Nov 95	5747	4527	121.46	602.61	0.5725
7	Dec 95	6668	4989	114.22	524.86	-0.4165
8	Jan 96	6552	4934	159.01	729.15	5.9212
9	Feb 96	6662	5142	152.80	692.56	5.0853
10	Mar 96	7023	5739	111.31	581.13	-0.8542
11	Apr 96	7037	5894	108.02	592.56	-1.3368
12	May 96	6641	5715	73.57	448.52	-6.2026
13	Jun 96	6025	5099	79.52	452.99	-5.1016

Table 4.3 Monthly Overall Performance Dataset (ADT)

Since AMC's sample size is huge and the monthly sample sizes (number of departure) vary, the author then chose to use $\overline{X}$ and S charts as the control chart s of choice to monitor delay times.

4.3.1 General Model for the $\overline{X}$ and S Chart. In this section, the author introduces the models for $\overline{X}$ and S Chart. Montgomery ((18):203) states that if $x_1, x_2 \cdots, x_n$ is a sample size of n, then the average of the sample is

$$\overline{x} = \frac{x_1 + x_2 + \cdots + x_n}{n} \tag{4.11}$$

Let $\overline{x_1}, \overline{x_2}, \cdots, \overline{x_m}$ be the averages of m such samples. In AMC's case, these would be the average delay times experienced over the 13-month period observed. The best estimator for μ, the process mean, is the grand mean as given by the following equation.

$$\overline{\overline{x}} = \frac{\overline{x_1} + \overline{x_2} + \cdots + \overline{x_m}}{m} \tag{4.12}$$

This $\overline{\overline{x}}$ will be the center line of $\overline{X}$ chart. Then the model for $\overline{X}$ chart is as follows.

$$UCL = \overline{\overline{x}} + Z_{\alpha/2} * \frac{\sigma}{\sqrt{n}} \tag{4.13}$$

$$\text{Center Line} = \overline{\overline{x}} \tag{4.14}$$

$$LCL = \overline{\overline{x}} - Z_{\alpha/2} * \frac{\sigma}{\sqrt{n}} \tag{4.15}$$

$$(4.16)$$

where $Z_{\alpha/2}$ is usually replaced by 3. The process standard deviation σ, must also be estimated from the past data. An estimate of σ is developed by first computing the standard deviation of each of the m samples and then computing, the average of the m standard deviations as follows:

$$\overline{S} = \frac{1}{m} * \sum_{i=1}^{m} S_i \tag{4.17}$$

Montgomery ((18):232) states S actually estimates $c_4 * \sigma$, where c_4 is a constant that depends on the sample size. He presents the associated c_4 values in ((18):Appendix VI). And when sample size, n, is greater than 25, the c_4 is calculated as $4(n-1)/(4n-3)$. An estimate of σ is thus given by s/c_4 and the resulting $\overline{X}$ chart has the form

$$\begin{aligned} UCL &= \overline{\overline{x}} + 3 * \frac{\overline{S}}{c_4\sqrt{n}} && (4.18)\\ \text{Center Line } &= \overline{\overline{x}} && (4.19)\\ LCL &= \overline{\overline{x}} - 3 * \frac{\overline{S}}{c_4\sqrt{n}} && (4.20)\\ & && (4.21) \end{aligned}$$

A control chart for the standard deviation of delay times is given by an S-chart

$$\begin{aligned} UCL &= \overline{S} + 3 * \frac{\overline{S}}{c_4} * \sqrt{1-c_4^2} && (4.22)\\ \text{Center Line } &= \overline{S} && (4.23)\\ LCL &= \overline{S} - 3 * \frac{\overline{S}}{c_4} * \sqrt{1-c_4^2} && (4.24)\\ & && (4.25) \end{aligned}$$

Actually, since the AMC data base consists not of actual delay times, but of delay time recorded to the nearest tenth of an hour. The means and standard deviations

of delays were approximated using the following "grouped data" formulas ((10):211):

$$ADT = \overline{x_i} = \frac{\sum_{j=1}^{p} f_j x_j}{\sum_{j=1}^{p} f_i} = \frac{\sum_{j=1}^{p} f_j x_j}{n} \tag{4.26}$$

$$S_i^2 = \frac{\sum_{j=1}^{p} f_j x_j^2 - (\sum_{j=1}^{p} f_j x_j)^2/n}{n-1} \tag{4.27}$$

where x_j denotes the median of the j^{th} "tenth" and f_j represents the number of delays of that duration.

The next potential problem is the sizes of the subgroups. Since AMC has different monthly numbers of missions. This means n changes from month to month. This factor indeed complicates the control chart model. However, three possible approaches to deal with these varying sizes are available here. They are charts with varying limits; charts with limits based on average sample size; standardized control charts. The author used the overall delay times to demonstrate each possible approach.

4.3.2 Chart with Varying Sample Sizes. The first approach is to create charts with varying control limits. Before doing so, however, we must account for these varying samples an those estimates of μ and σ. Montgomery ((18):235) states that when the sample sizes are variable, then use

$$\overline{\overline{x}} = \frac{\sum_{i=1}^{m} n_i \overline{x_i}}{\sum_{i=1}^{m} n_i} \tag{4.28}$$

$$\overline{S} = \sqrt{\left(\frac{\sum_{i=1}^{m}(n_i - 1)S_i^2}{\sum_{i=1}^{m} n_i - m}\right)} \tag{4.29}$$

to estimate μ and σ. In AMC's case, we have

$$\overline{S} \;=\; \sqrt{\frac{(6028-1)*391.6788^2 + \cdots + (6025-1)*547*452.9952^2}{(6028+\cdots+6025)-13}} \doteq 572.3941$$

$$\begin{aligned}
\overline{\overline{x}} &= \frac{6028 * 116.1194 + \cdots + 6025 * 79.52}{84414} \doteq 117.1813 \\
c_4 &\approx 4 * (6028 - 1)/(4 * 6028 - 3) \doteq .9999585
\end{aligned}$$

Since the control limits will differ from sample to sample, the author picked June and July 95 to demonstrate the calculation. Hence, for June 95, the S chart,

$$\begin{aligned}
UCL &= 572.3941 + 3 * \frac{572.3941}{0.9999585} * \sqrt{1 - 0.9999585^2} \doteq 588.0348 \\
\text{Center Line} &= 572.3941 \\
LCL &= 572.3941 - 3 * \frac{572.3941}{0.9999585} * \sqrt{1 - 0.9999585^2} \doteq 556.7534
\end{aligned}$$

where we also have computed

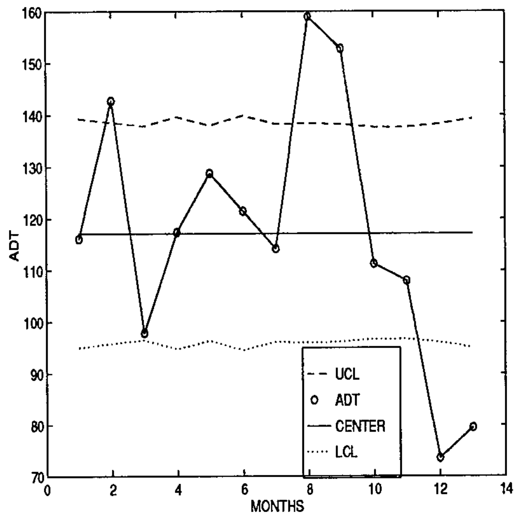
$$c_4 \approx 4 * (6028 - 1)/(4 * 6028 - 3) \doteq .9999585$$

For $\overline{x}$ chart,

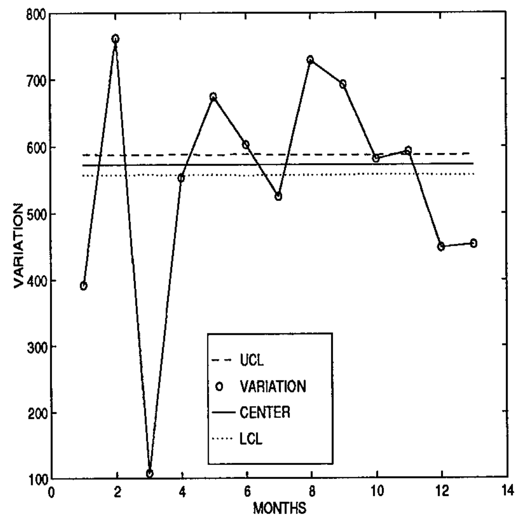
$$\begin{aligned}
UCL &= 117.1813 + 3 * \frac{572.9285}{0.9999585\sqrt{6028}} \doteq 139.3371 \\
\text{Center Line} &= 117.1813 \\
LCL &= 117.1813 - 3 * \frac{572.9285}{0.9999585\sqrt{6028}} \doteq 95.0640
\end{aligned}$$

While in July 95, the S chart, $c_4 \approx 4 * (6458 - 1)/(4 * 6458 - 3) \doteq .9999612$

$$\begin{aligned}
UCL &= 572.3941 + 3 * \frac{572.3941}{0.9999612} * \sqrt{1 - 0.9999612^2} \doteq 587.5038 \\
\text{Center Line} &= 572.3941 \\
LCL &= 572.3941 - 3 * \frac{572.3941}{0.9999612} * \sqrt{1 - 0.9999612^2} \doteq 557.2844
\end{aligned}$$



(a)



(b)

Figure 4.4 The Control Charts with varying limits on ADT : (a)$\overline{X}$ (b) S

For $\overline{x}$ chart,

$$
\begin{aligned}
UCL &= 117.1813 + 3 * \frac{572.9285}{0.9999612\sqrt{6459}} \doteq 138.5851 \\
\text{Center Line} &= 117.1813 \\
LCL &= 117.1813 - 3 * \frac{572.9285}{0.9999612\sqrt{6459}} \doteq 95.8147
\end{aligned}
$$

Control charts with varying limits for the overall performance are shown in Figure 4.4. "1" on the horizontal axis stands for June 1995, and so on. Based on these, August 1995 has the smallest standard deviation. In general, the standard deviation of AMC's overall performance is out of control.

4.3.3 The $\overline{X}$ and S Chart Based on the Average Sample Size. The second approach is to use control charts with limits based on the average sample size. Because there are 84414 missions over this 13 month period, the average sample size is $84414/13 \doteq 6493$. The value of c_4 is calculated as $4*(6493-1)/(4*6493-3) \doteq$

0.999961 for each month. For AMC overall performance, the monthly ADT is the mean of each sample. Then the S chart model is

$$\begin{aligned}
UCL &= 572.3941 + 3 * \frac{572.3941}{0.999961} * \sqrt{1 - 0.999961^2} \doteq 587.4642 \\
\text{Center Line} &= 572.3941 \\
UCL &= 572.3941 - 3 * \frac{572.3941}{0.999961} * \sqrt{1 - 0.999961^2} \doteq 557.324
\end{aligned}$$

The $\overline{X}$ chart model is

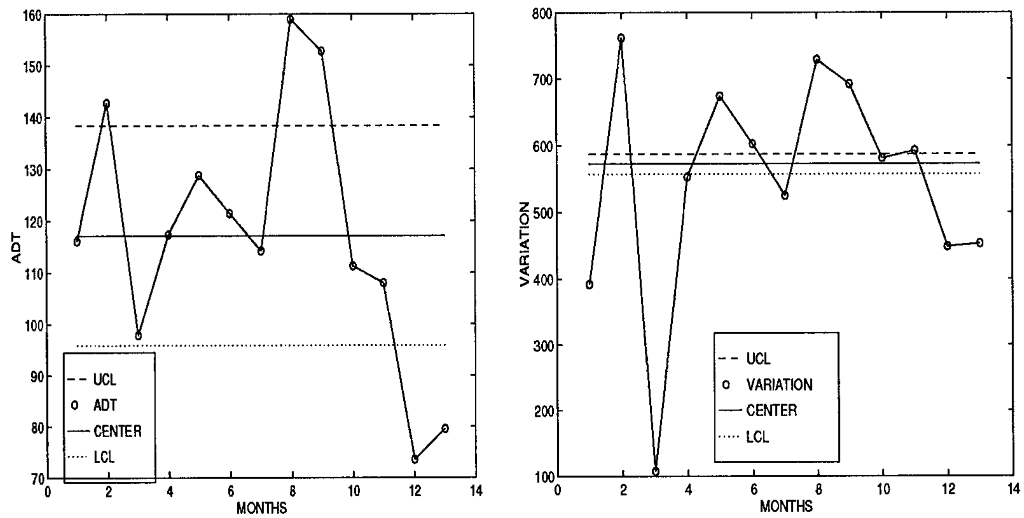
$$\begin{aligned}
UCL &= 117.1813 + 3 * \frac{572.3941}{.999961\sqrt{6493}} \doteq 138.4558 \\
\text{Center Line} &= 117.1813 \\
UCL &= 117.1813 - 3 * \frac{572.3941}{.999961\sqrt{6493}} \doteq 95.8360
\end{aligned}$$

By taking this approach, the $\overline{x}$ and S charts have same control limits over 13 month period. The control charts are shown in Figure 4.5.

4.3.4 The Standardized Control Chart. The third approach is to use standardized control charts. This approach converts the monthly observations into standardized units by the following:

$$Z_i = \frac{x_i - \overline{\overline{x}}}{\overline{S}/\sqrt{n_i}} \tag{4.30}$$

For the $\overline{x}$ chart, the UCL and LCL are assigned as ± 3. The 6th column in Table 4.3 lists the standardized values for the overall performance. The S chart here is the one with varying limits. The author still pick Jun 95 as an example to demonstrate the calculation of standardized values.



(a) (b)

Figure 4.5 The Control Charts with Limits Based on Average Sample Size on ADT : (a)$\overline{X}$ (b) S

$$
\begin{aligned}
UCL &= 3 \\
\text{mean} &= 0 \\
LCL &= -3 \\
Z &= \frac{(116.11 - 117.1813)}{572.3941/\sqrt{6028}} \doteq -.13923
\end{aligned}
$$

Figure 4.6 shows the standardized $\overline{x}$ control chart for overall performance.

4.3.5 Interpretation of Results. Interpretation of Results. The most striking aspects of the X-bar and S-charts constructed in the previous sections is that they exhibit extreme evidence of an out-of-control process. Indeed, the X-bar chart shows 5 of the 13 points out of control while the S-chart has all points out of control and oscillating wildly around a relatively narrow in-control region. This should lead

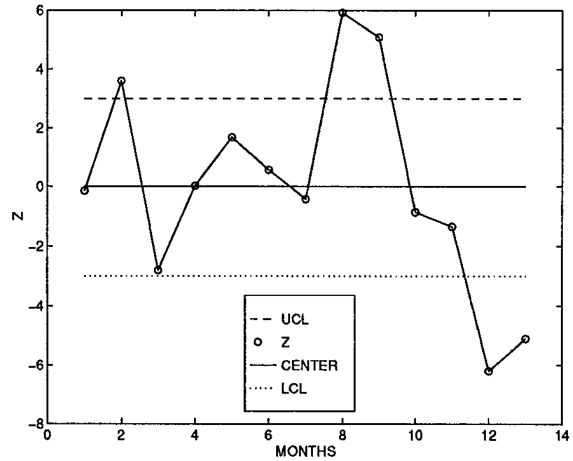


Figure 4.6 The standardized $\overline{X}$ Control Chart on ADT

one to question either the behavior of the process or the validity of the charts.

The behavior of the X-bar chart is the least extreme of the two and in somewhat consistent with the behavior observed in the P-charts for DR. For example, the steep decline in ADT over the last five months coincides with a relatively steep increase in DR over the same time span. This is not surprising since the average delay time should logically be negatively correlated with the proportion of on-time departures (that, of course, have delays less than 15 minutes). As with the P-charts, the search for the causes for these significant changes in delay times could lead analysts to the identification of assignable causes for delay that could perhaps be eliminated.

The behavior of the S-chart is somewhat distressing however since the points plotted do not even come close to falling within the control limits. Indeed, the wildness of this behavior was so great that the author decided to double check the S-chart procedure by also constructing a control chart on the process variance using an S^2-Chart.

An S^2-Chart is based on the fact that, if the original observation are normally distributed, then the sample variances have a distribution that is proportional to that of Chi-square distribution with $n-1$ degree of freedom. The control limits for

the resulting S^2-chart are

$$UCL = \overline{S}\chi^2_{\alpha/2,n-1}/(n-1) \tag{4.31}$$

$$\text{CL} = \overline{S} \tag{4.32}$$

$$LCL = \overline{S}\chi^2_{1-\alpha/2,n-1}/(n-1) \tag{4.33}$$

$$\tag{4.34}$$

where $\chi^2_{\alpha/2,n-1}$ and $\chi^2_{1-\alpha/2,n-1}$ denote the upper and lower $\alpha/2$ percentage points of the Chi-square distribution with $n-1$ degree of freedom. Using the average sample size of 6493 and $\alpha = 0.01$, these become for the AMC data,

$$\begin{aligned} UCL &= 312822 \\ \text{CL} &= 327635 \\ LCL &= 342448 \end{aligned}$$

As seen in Figure 4.7, the same wild behavior observed, confirming the construction of the S-chart was indeed correct. This wild behavior could perhaps indicate that significant assignable cause variation is inducing major changes in the standard deviation of delay times from month to month.

However, before jumping to that conclusion, it is wise to ask whether or not the assumption behind the S-chart (and the $\overline{x}$ and S^2-charts are met. In particular, the S-chart and the S^2 are firmly rooted in the assumption that individual observations are normally distributed.) Since the observations with the departure process are delay time and, on the average about 80% of these are zero (or very close to it), it seems very clear that this normality assumption is not met. This is further corroborated by the fact that sample coefficient of variation (the ratio of the sample standard deviation to the sample mean) of delay time varies appreciably from month to month,

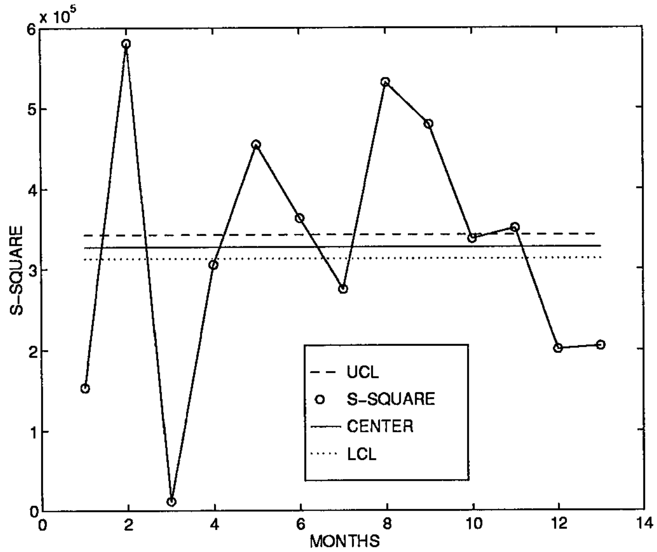


Figure 4.7 S^2 Chart

ranging from 1.1 to 6.1. The fact that these are all larger than one, and most are larger than three, very strongly suggests that overall delay times follow a highly skewed, non normal distribution.

In addition, another assumption made in construction of the $\overline{x}$, S-chart and the S^2 chart is that the mean and variance of distribution of delay time do not change from month to month. Since the proportion of on-time departure is not in control, and thus appear to be changing from month to month, it is doubtful that this assumption is met either. To see this, consider a simple model in which all on-time departures experience exactly zero delay and in which the delay time for a departure that is delayed is random variable with a mean of 600 minutes and a standard deviation of 1286 minutes. (that is, the delay times for delayed departures are in control since their distribution does not change from month to month. (It then follows that the mean and standard deviation of the delay time, D, any departure selected in advanced of knowing whether or not it will be delayed is a random variable

p	Mean delay time given that an aircraft is delayed	Standard deviation of delay time given that an aircraft is delayed	E(D) Overall mean	Var(D)	SD(D)
0.75	600	1286	150	413281	643
0.76	600	1286	144	396750	630
0.77	600	1286	138	380219	617
0.78	600	1286	132	363688	603
0.79	600	1286	126	347156	589
0.80	600	1286	120	330625	575
0.81	600	1286	114	314094	560
0.82	600	1286	108	297563	545
0.83	600	1286	102	281031	530
0.84	600	1286	96	264500	514
0.85	600	1286	90	247969	498

Table 4.4 Relationship Between DR and ADT

with the following mean, variance, and standard deviation:

$$
\begin{aligned}
E(D) &= 0 * p + (1-p) * 600 = 600 * (1-p) \\
Var(D) &= 0 * p + (1-p) * (1286)^2 \\
\sqrt{VarD} &= 1286 * \sqrt{(1-p)}
\end{aligned}
$$

Then, the effect of change in the proportion of on-time departures can be summarized as in Table 3.6. This table clearly depicts the fact that the distribution of overall delay time changes substantially with the proportion of on-time departure. Thus, if this proportion is changing from month to month, then the distribution of overall delay times will also be changing from month to month. This suggests that control charts for monitoring overall delay times may not be appropriate. This situation clearly warrants further study.

In summary, the extreme behavior of the sample standard deviation is very interesting but, rather unfortunately, was discovered very late in the development of this thesis. As a result, the author was unable to definitively address and resolve these issue. A possible alternative might be to develop charts on the mean and standard deviation of the delay times only for those aircraft that do not depart on time.

4.4 *The Exponential Weighted Moving Average Control Chart*

Because Shewhart charts only use the information in the last plotted point, the effect of the previous points is not considered at all, except when additional run rules are applied. As a result, Montgomery ((18):279) states, " A Shewhart control chart is relatively insensitive to a small shift in the process." This means that Shewhart charts are relatively weak in detecting small changes in the process mean. The exponentially weighted moving average (EWMA) control chart is designed for detecting small shifts.

As mentioned earlier, the author chose the standardized chart to deal with the varying sizes of subgroups. In this section, the author will apply EWMAs to the overall performance and C-5 performance data to demonstrate their use for two different MOEs

4.4.1 *Formulas for the EWMA.*

Montgomery ((18):299) defines the exponential weighted moving average as:

$$Z_t = \lambda * \overline{X_t} + (1-\lambda) * Z_{t-1} \tag{4.35}$$

where $0 < \lambda \leq 1$, and the starting value is $Z_0 = \overline{\overline{X}}$. In an EWMA, the $Z_t's$ are plotted against the following control limits ((18),p301):

$$UCL = \overline{\overline{X}} + 3 * \sigma * \sqrt{\frac{\lambda}{(2-\lambda) * n}} \tag{4.36}$$

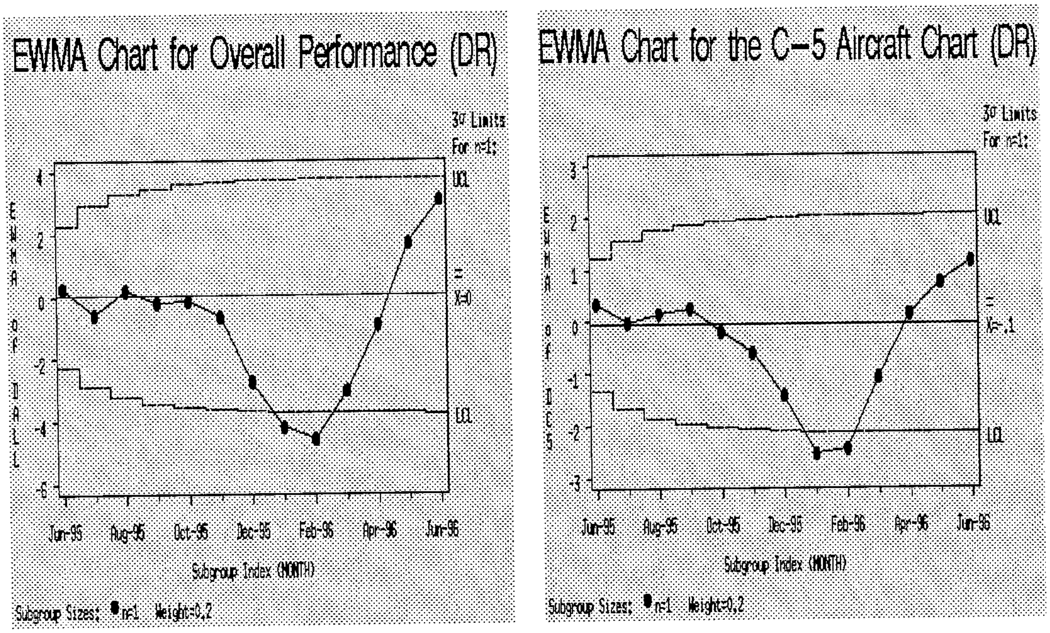
$$\text{Center Line} = \overline{\overline{X}} \tag{4.37}$$

$$LCL = \overline{\overline{X}} - 3 * \sigma * \sqrt{\frac{\lambda}{(2-\lambda) * n}} \tag{4.38}$$

(4.39)

4.4.2 *Results for DR.*

Montgomery states that the parameter λ should be selected such that $0.05 \leq \lambda \leq 0.25$. The author followed Montgomery's suggestion



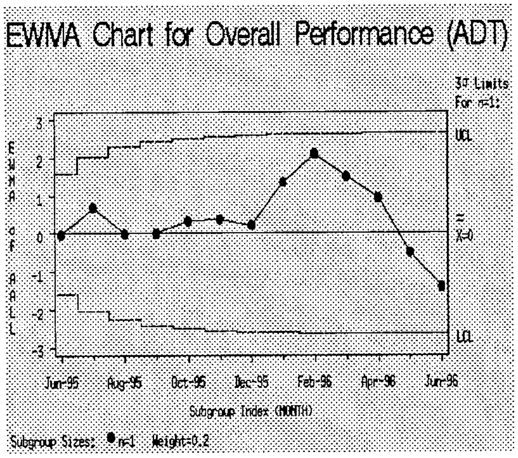
(a) (b)

Figure 4.8 EWMA Charts for DR with Different Weight Number=0.2: (a)Overall Performance (b)The C-5 Aircraft

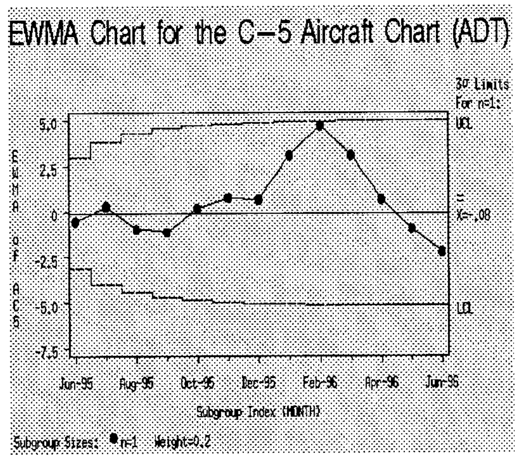
and picked four values for λ in that approximate range to compare the differences between them. These λ values are $\lambda = 0.08$, $\lambda = 0.1$, $\lambda = 0.2$, and $\lambda = 0.3$. They are applied to the overall DR and C-5 DR performance data. The author presented the figures with $\lambda = 0.2$ for overall DR and the C-5 DR performance, as shown in Figure 4.8, in the section. The remainders are in Figure B.1 to B.3 in Appendix B.

4.4.3 The Results for Average Delay Time. Following the same procedures as in the previous section, EWMA's are computed on the standardized value, of ADT using weight of 0.08, 0.1, 0.2 and 0.3. The EWMA charts with $\lambda = 0.2$ is demonstrated in Figure 4.9. The remainders are shown in Figure B.4 to B.6 Appendix B.

Since we have doubts about the use of overall delay time as an appropriate value to be charting, these results are strictly notional and are presented for demonstration purposes only.



(a)



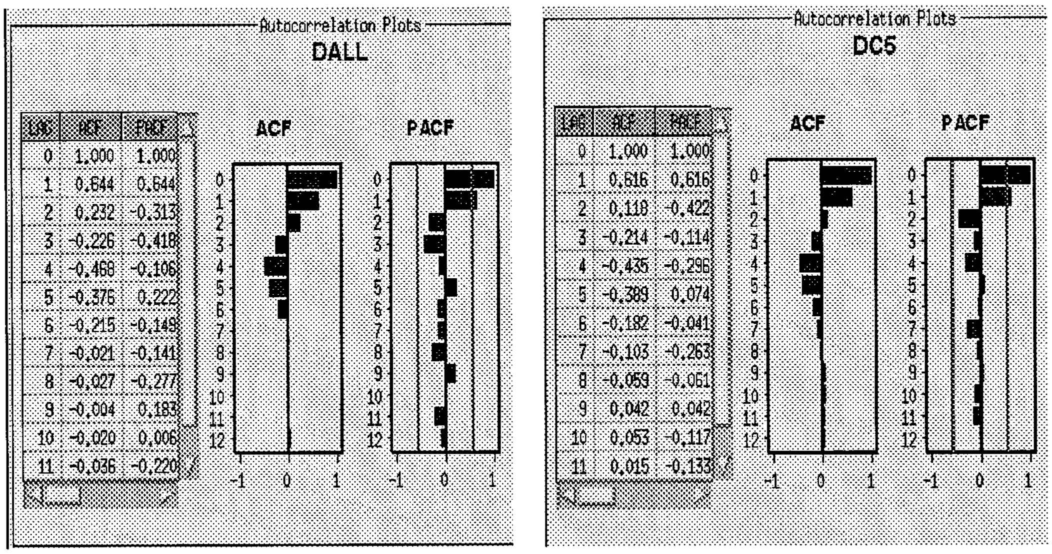
(b)

Figure 4.9 EWMA Charts for ADT Time Series with Weight=0.2 (a)Overall Performance (b) The C-5 Aircraft

4.5 The Autocorrelation Function

Zalewski ((14):28) stated that "autocorrelation is a measure of the tendency of neighboring observations from a time-series to vary linearly together rather than independently." Hence, the autocorrelation in the time series data can cause misleading conclusions when applying control charts. Makridakis, Wheelwright, McGee ((16):364) also stated, "the key statistics in time series analysis is the autocorrelation coefficient." Thus, to know if the autocorrelation is significant or not is very important before making a final conclusion on the results from Shewhart charts. The author used the autocorrelation function (ACF) and partial autocorrelation (PACF) to verify if autocorrelation exists in the time series used in this thesis. SAS "proc arima" procedure provides the ACF and PACF values. The ACF depicts the autocorrelations of lag K_i, which measure of the degree of dependence between observations that are K time periods above, as a function of the lag K. In particular, it is a plot of Γ_k verse Γ where

$$r_k = \frac{\sum_{t=2}^{n}(Y_t - \overline{Y})(Y_{t+k} - \overline{Y})}{\sum_{t=1}^{n} Y_t - \overline{Y}^2} \qquad (4.40)$$



(a) (b)

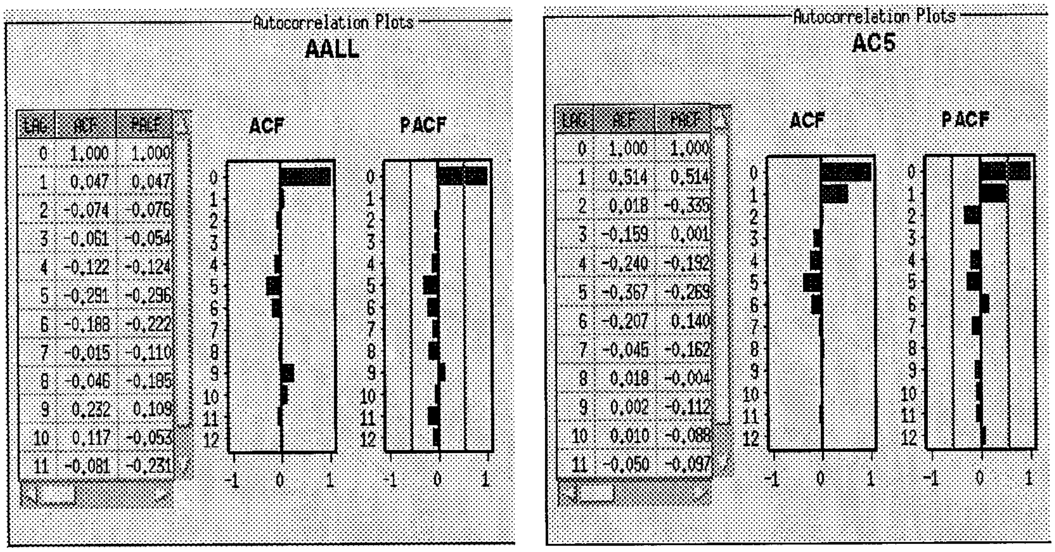
Figure 4.10 The ACF and PACF of DR Time Series : (a)Overall Performance (b) The C-5 Aircraft

(4.41)

and where the Y_t is the t_{th} observation in the time series and $\overline{Y}$ is the average of $Y_1, Y_2, \cdots, Y_3$ ((16):366). (The derivation of the PACF is beyond of this thesis and is not included here, although plots of it are shown for completeness. See (16) for a complete discussion. SAS "proc arima" procedure ((21):141) uses $1/\sqrt{n}$ to calculate the standard deviation of the lag k autocorrelation. In this case, the values of γ_k in excess of $2/\sqrt{n} = 2/\sqrt{13} = .5547$, as assumed to be significant different from zero.

Because there are four time series of standardized Z values used in this series, the author used SAS ((23):92) to demonstrate the ACF and PACF for each time series. Figure 4.10 shows the ACF and PACF for the DR time series, Figure 4.11 for the ADT time series.

Based on Figures 4.10 and 4.11, the autocorrelations in the two DR time series are both significant at lag 1. This suggests that there is significant autocorrelation present from month to month, rendering conclusion based on the P-chart uncertain.



(a) (b)

Figure 4.11 The ACF and PACF of ADT Time Series : (a)Overall Performance (b) The C-5 Aircraft

However, this conclusion of significance should be tempered by the fact that there are only 13 monthly observations, a very small sample for the purpose of estimating an autocorrelation. If significant autocorrelation is present, control chart methods that explictly account for it, such as an exponential-weighted moving average chart with a center line ((18):347) should be used.

4.6 *Average Run lengths*

The performance of a control chart is often assessed in relation to what is called its "average run length" characteristics. Simply stated, the average run length (ARL) is the number of samples that are expected to be observed and charted until a point plotting outside the control limits is obtained. When the process is in control, the ARL is the expected number of samples between false alarms. When the process is out of control, the ARL is the expected number of samples required to detect the presence of the associated assignable cause. In this section, we develop formulas for computing ARL for P-Charts and show how they can be applied to help determine

the best reporting frequency for DR.

Suppose a P-chart is developed for a departure process whose in-control proportion of on time departures is p_0. Based on a sample of n departures, the control limits for this chart are

$$\begin{aligned}
\text{LCL} &= p_0 - 3 * \sqrt{\frac{p_0 * (1-p_0)}{n}} \\
\overline{CL} &= p_0 \\
\text{UCL} &= p_0 + 3 * \sqrt{\frac{p_0 * (1-p_0)}{n}}
\end{aligned}$$

The in-control average run length for this chart is determined by first computing the probability that a point plots outside these control limits when the process is in control. Letting X and $\hat{p}$, respectively, denote the number and proportion of delays experienced in n departures, the probability can be written as: P[point plots outside control limits]

$$\begin{aligned}
&= P[\hat{p} < \text{LCL or } \hat{p} > UCL] \\
&= P[X < \text{nLCL or X} > nUCL] \\
&= P[X < nLCL] + P[X > nUCL] \\
&= \textstyle\sum_{x=0}^{[nLCL]} \binom{n}{x} p_0^x (1-p_0)^{n-x} + \sum_{[nUCL]+1}^{n} \binom{n}{x} p_0^x (1-p_0)^{n-x}
\end{aligned}$$

where $[y]$ denotes the greatest integer contained in the real number y. When the sample size and on-time proportion are such that $1/(n+1) < p < n/(n+1)$, this can be approximated with

$$\text{P[point plots outside control limits]} = \Phi(\frac{nLCL - np_0}{\sqrt{np_o(1-p_0)}}) + 1 - \Phi(\frac{nUCL - np_0}{\sqrt{np_o(1-p_0)}})$$

When n and p satisfy the preceding relationship and 3-sigma control limits are used,

$$\text{P[point plots outside control limits]} = \Phi(-3) + 1 - \Phi(3) = 0.0027$$

Likewise, when an assignable cause shifts the proportion of on-time departures to a new level, say p_1, the probability that a point plots outside the control limits is computed similarly as

$$\text{P[point plots outside control limits]} = P[X < nLCL] + P[X > nUCL]$$

Assuming independence between months, the average run length in either case is simply the reciprocal of this probability, i.e.,

$$ARL = 1/P\text{[point plots outside the control limits]}$$

To demonstrate how these might be used in determining an optimal reporting frequency for DR, suppose $p_0 = 0.85$ and one is interested in being able to detect a shift in overall DR of 0.01. Also assume for simplicity that exactly 6400 departures occur each and every month. Table 4.5 displays the behavior of ARL as a function of the reporting frequency. Table 4.6 displays the reporting frequency.

Reporting Frequency num/mon	Sample Size	LCL	UCL	p[points outside control limits] $p_1 = 0.84$ -0.1 Shift	$p_0 = 0.85$ in control	$p_1 = 0.86$ 0.1 shift
0.5	12800	0.8405	0.8595	0.5662	0.0027	0.5688
1	6400	0.8366	0.8634	0.2297	0.0027	0.2172
2	3200	0.8311	0.8689	0.0840	0.0027	0.726
4	1600	0.8232	0.8768	0.0336	0.0027	0.0265

Table 4.5 ARL Table

Reporting Frequency		Average Run Length (Number of Samples)			Average Run Length (Month)		
Number of times	Sample	$DR = 0.84$	$DR = 0.85$	$DR = 0.86$	$DR = 0.84$	$DR = 0.85$	$DR = 0.86$
Per month	Size	-0.1 shift	in control	0.1 shift	-0.1 shift	in control	0.1 shift
0.5	12800	1.77	370.38	1.76	3.54	740.76	3.52
1	6400	4.35	370.38	4.6	4.35	370.38	4.6
2	3200	11.91	370.38	13.78	5.96	185.19	6.89
4	1600	29.77	370.88	37.68	7.44	92.59	9.42

Table 4.6 ARL Table

A more general ARL table for EWMA was adapted from SAS manual ((22):589) and is listed in Appendix C.

V. *Process Capability Analysis*

Thus far, in both Pareto analysis and control charting, the performance of AMC's departure processes have been examined independent of any goals or standards for performance. However, AMC has established 85% departure reliability as a command level-wide goal and it is natural to evaluate the Command's performance relative to this goal. In traditional application of statistical process control, process capability analysis and process capability measures provide a well-established means of evaluating the performance of a process relative to performance specifications. The objective of this section of this thesis is to examine their applicability to AMC's departure processes.

5.1 Principal of Process Capability Analysis

When control charts are applied, only if a process is "in control" or "out of control" can be determined. Whether the process meets its specifications or not can not be known from a control chart. This is where process capability comes into play. Zalewski made the following statement about process capability ((14):14):

> While the control chart indicates the state of statistical control, it does not indicate how suitable the output of the process is for its intended purpose. Process capability is a measure of suitability, and hence, also measures the quality of a process.

5.1.1 Specification Limits. In order to calculate process capability index, a target value and upper and lower specification limits (USL and LSL) must be provided for the quality characteristic of interest. Additionally, assume that the desired performance of AMC's departure processes can be described by upper and lower specification limits denoted, USL and LSL respectively, which are requirements on a measured quality characteristic. When the quality characteristic is the proportion of on-time departures, a reasonable lower specification limits would be the Command's

85% DR goal. The upper limit implicitly would be 100% on time performance. When the quality characteristic is delay time, no explicit specifications are obvious or available. However, one could perhaps consider a 15-minute delay to represent an upper limit on acceptable performance (since departures within 15 minutes of schedule are considered on-time). A lower specification limit would be zero delay.

These possible specifications seem reasonable at an overall Command level. However, as mentioned earlier, on-time performance is pretty much a function of the age of the corresponding aircraft. With this in mind, it is perhaps also reasonable to suggest that different specifications could be set for different types of aircraft, as long as these both are realistic for each type of aircraft and consistent with the overall Command goal. Consistency with the Command goal can be maintained by use of the following formula (whose derivation is given in Appendix D).

$$DR_{overall} = \sum_{i=1}^{5} P_i * DR_i \tag{5.1}$$

where P_i is the proportion of missions flown by the i_{th} type of aircraft, and DR_i is the departure reliability of the ith type of aircraft. As a straightforward example, suppose there were simply two types of aircraft, "old" and "new." If old aircraft account for 60% of all departures, then lower specification limits of 80% DR for old aircraft and 92.5% for new aircraft would produce an overall DR of 85%, since

$$(0.6) * (0.8) + (0.4) * (0.925) = 0.85$$

In terms of the aircraft flown by AMC, and using the proportions of missions historically, possible specifications for the different type of aircraft are the C-5 = 81%, C-17 = 95%, C-141 = 84%, KC-10 = 85%, and KC-135 = 88%. This set of specification will produce

$$(.16) * (.81) + (.06) * (.95) + (.44) * (.84) + (.10) * (.85) + (.24) * (.88) \doteq .852$$

However, the setting of realistic limits for AMC processes would require careful analysis and the judgment of domain experts. The above two examples are provided only to demonstrate this idea.

Statistically hypothesis testing is an important methodology that could be used to formally test if performance meets specifications. The following example to demonstrate the use of hypothesis testing in relation to a performance goal.

Consider AMC's DR goal of 85%. One possible test of this goal would be to evaluate the hypothesis

$$H_0: \quad P = 0.85$$
$$H_a: \quad P \neq 0.85$$

where p is the probability that an aircraft departures on-time. To test these hypothesis, one would observe the proportion of on-time departures, $\hat{P}$, in a sample of n departures and compute the test statistic

$$Z = \frac{\hat{P} - 0.85}{\sqrt{0.85 * (1 - 0.85)/n}}$$

and rejected the hypothesis that $p = 0.85$ if $|Z| > Z_{\alpha/2}$. This region is selected so that if the null hypothesis test H_0 is true, there would be a $100\alpha\%$ chance of its being falsely rejected. As an example, consider testing whether or not the KC-10 aircraft is meeting this performance standard. Of the 8,066 KC-10 departures observed in the AMPAS database, there were 1,237 delays, yielding $\hat{p} = 0.8466$. The corresponding test statistic is

$$Z = \frac{0.8466 - 0.85}{\sqrt{0.85 * (1 - 0.85)/8066}} \approx -0.8451$$

Since $|Z| = 0.8451 < 1.96 = Z_{0.025}$, we fail to reject the hypothesis test that $p = 0.85$ at the $\alpha = 0.05$ level of significance. In other words, the observed DR of 84.66% is not significantly different from Command goal of 85%.

5.1.2 Process Capability Measures. Measures of process capability generally attempt to relate specification limits to the natural tolerance limits of the quality characteristic in question. These natural tolerance limits are defined by the range of values that most measurements are expected to fall in when a process is in control. There are usually defined by

$$\text{LNTL} = \mu_0 - 3\sigma_0 \tag{5.2}$$

$$\text{UNTL} = \mu_o + 3\sigma_0 \tag{5.3}$$

where μ_0 is the in-control process mean and σ_0 is the in-control process standard deviation. If it can be assumed that measurements are normally distributed, then 99.73% of all observations with fall within these natural tolerance limits. If specification are such that $LSL < LNTL$ and $USL > UNTL$, then when the process is in control, most measured values of the quality characteristic will conform to specifications.

The simplest measurement of process capability used in SPC practice is the process capability ratio ((18):370), which relates the width of the specification interval to the width of the natural tolerance interval. Montgomery ((18):366) states it is customary to use the $6\sigma_0$ spread in the natural tolerance limits of the product quality characteristic as a measure of process capability. This process capability ratio is defined as

$$\text{PCR} = \frac{\text{USL-LSL}}{6\sigma_0}$$

This ratio obviously assumes that both upper and lower specification limits are given; if only a one-sided specification is given, one sided versions of PCR can be computed via

$$PCR_u = \frac{USL - \mu}{3 * \sigma} \tag{5.4}$$

$$PCR_l = \frac{\mu - LSL}{3 * \sigma} \tag{5.5}$$

$$\tag{5.6}$$

As should be obvious from these formulas, PCR attempts to measure the specification limits in relation to the natural tolerance limits. However, as Montgomery ((18):373) states, PCR "does not take into account where the process mean is located relative to the specification limits." To explicitly account for relative centers of the specification and natural tolerance limits, another widely-used measure is given the process capability index computed by

$$PCR_k = MIN(PCR_u, PCR_l) \tag{5.7}$$

Obviously, PCR_k[1] is simply the one-sided PCR for the specification limit nearest the in control process mean. The resulting PCR_k index provides objective standard upon which the performance of a process can be evaluated with respect to its requirements.

5.1.3 Applicability to AMC Processes. The process capability measures computed in the previous section implicitly assume that the quality characteristic being monitored is a variables-type measurement with a known (or estimable) in control process mean and standard deviation. Further, their usual interpretation is based on the assumption that observations of this quality characteristic are normally distributed. Specifically, they are often used to estimate the "process fallout," which

[1] also called C_{PK}

is simply proportion of observations that do not meet specifications. Table 5.1, which is adapted from Montgomery ((18):372), shows their relationship for a normally distributed quality characteristic.

	Process Fallout (in defective percent	
PCR	One-side Specification	Two-sided Specification
0.25	22.6628%	45.3255%
0.5	6.6807%	13.3614%
0.6	3.5931%	7.1861%
0.7	1.7865%	3.5729%
0.8	0.8198%	1.6395%
0.9	0.3467%	0.6934%
1.0	0.1350%	0.2700%
1.1	0.0484%	0.0967%
1.2	0.0159%	0.0318%
1.3	0.0048%	0.0096%
1.4	0.0014%	0.0027%
1.5	0.0004%	0.0007%
1.6	0.0001%	0.0002%
1.7	0.000017%	0.000034%
1.8	0.000003%	0.000006%
2.0	0.00000009%	0.0000018%

Table 5.1 Percentages of the Process-capability ratio (PCR) and associated process fallout for a normality distributed process

Because AMC has the AMPAS database with which to track the DR process, fallout can be computed exactly and need not be estimated. Hence, the use of process capability to estimate the fallout is not necessary. Even if it were necessary, the standard process capability approach would not be appropriate because delay times obviously do not have normal distribution. The author uses Figure 5.1 to show the distribution of the delay time for the C-17 aircraft. There are 5300 missions over this 13-month period. Note that most observations fall in the first bar width, which is between 0 to 90 minutes. The author considered the ADT over 1800 minutes are outliers because the average delay time for each departure spread out very much. It is hard to catch every sample and demonstrate the distribution at the same time. Those departures do not show in this figure. Actually, even those departures are included in this figure, it can still barely see them because their frequency is so small compared to the first bar. By doing this, it is easier to show the other departures whose ADT are less than 1800 minutes. Actually, plotting the outliers does not change the shape of the distribution at all.

This shape of distribution is assumed to be typical of other subgroups, because

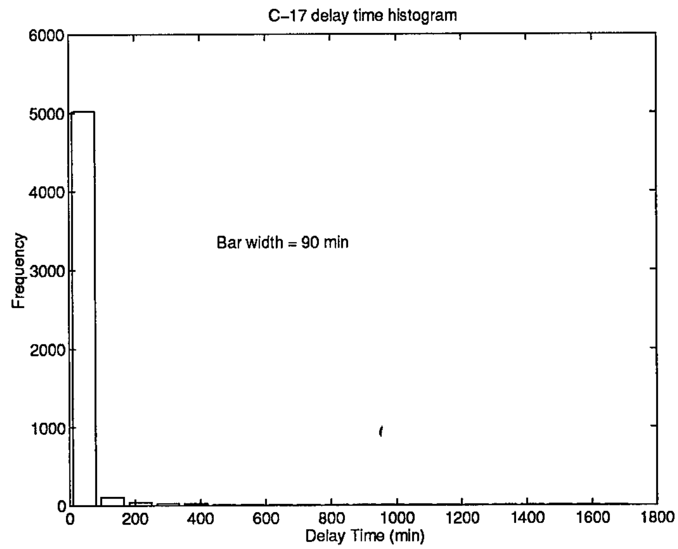


Figure 5.1 Histogram for the Distribution of the C-17 Process

even for the group with the worst DR (the C-5 subgroup), 70 percent of all departures are on-time. Thus, histogram of delay time will have a huge spike in their first cell. This histogram clearly shows that delay times does not have a normal distribution at all.

5.1.4 Normal Probability Plotting. Another alternative way to test the normality is the normal probability plotting, which is a graph of the ranked data verses the sample cumulative percentage. Montgomery ((18):380) states, " probability plotting has the advantage that it is unnecessary to divide the range of the variable into class levels, and it produces reasonable results for the moderately small samples (which the histogram will not)." The formulas ((18):381) to constructed the plotting P_j of the observation with rank j is calculated as follows:

$$P_j = \frac{j - 0.5}{n} \tag{5.8}$$

where n is the sample size. The author will use the 13 monthly standardized values to demonstrate this computation. Table 5.2 shows the rank of this DR overall performance series.

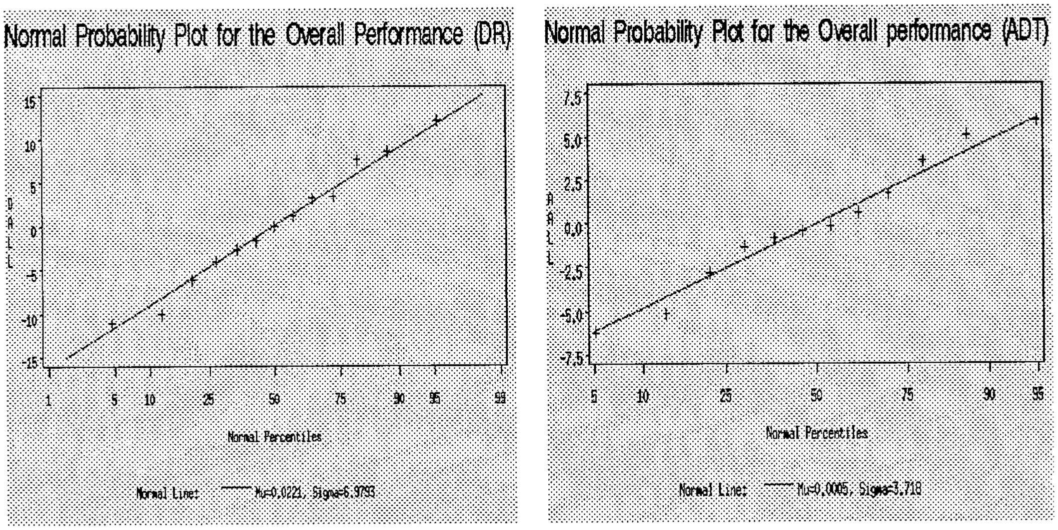
Rank	1	2	3	4	5	6	7
Z Values	-11.065	-9.953	-6.144	-4.033	-2.663	-1.728	0
Plotting Position	0.038462	0.115285	0.192308	0.269231	0.346154	0.423077	0.5
Rank	8	9	10	11	12	13	
Z Values	1.169	3.154	3.337	7.57	8.57	12.065	
Plotting Position	0.576923	0.653846	0.730769	0.807692	0.884615	0.961538	

Table 5.2 Normal Probability Dataset for DR Standardized Values

Considering number one Z DR value $P_1 = (1 - 0.5)/13 \doteq 0.03846$ and $P_2 = (2 - 0.5)/13 \doteq .11528$, etc The normality probability plot for this series is shown in Figure 5.2, part (a). The horizontal axis is the scale of normal percentage, vertical axis is the scale for the Z values. Hence, the second row in Table 5.2 is the values of x axis for the plotted points, and the third row in Table 5.2 is the values of y axis for the plotted points. Montgomery ((18):381) states that the straight line in normal probability plot is fit by eye. When drawing that fitted line, it is best to give more emphasis to the center points on the graph rather than the extremes. He ((18):382) also states, that the mean of the normal distribution is the fiftieth percentile, the standard deviation is the slope of the straight line, and the estimation of the standard deviation is the difference between the 84th and 50th percentile.

The decision rules is that if all the plotted points lie nearly along a straight line, this indicates that this distribution has normal distribution. Normal probability plots, created by SAS, are shown in Figure 5.2. Base on Figure 5.2, part (a), DR (Z values) has a pretty good normal distribution.

As to the Z values from the ADT, Table 5.3 shows the normality probability plot information. The plot is shown in Figure 5.2, part (b). The values at second row in Table 5.3 are the vertical values of plotted points in Figure 5.2, part (b). The values at third row are the horizontal values in Figure 5.2, part (b). Based on the results, this series also forms an all right normal distribution.



(a) (b)

Figure 5.2 Normal Probability Plot for Z values of Overall Performance (a) Monthly DR Values (b) Monthly ADT Values

Rank	1	2	3	4	5	6	7
Z Values	-6.20264	-5.1016	-2.79908	-1.33684	-0.85429	-0.41658	-0.13923
Plotting Position	0.038462	0.115285	0.192308	0.269231	0.346154	0.423077	0.5
Rank	8	9	10	11	12	13	
Z Values	0.031211	0.572516	1.679263	3.5981	5.085315	5.92125	
Plotting Position	0.576923	0.653846	0.730769	0.807692	0.884615	0.961538	

Table 5.3 Normal Probability Dataset for ADT Standardized Values

VI. Summary and Recommendations

This chapter summarizes the results of this thesis in relation to the three specific objectives in outlined Section 1.2, recommendations and future work.

6.1 Conclusion

The following SPC methods were evaluated in this thesis: cause and effect diagrams, Pareto analysis, control charts, and process capability analysis. Except for process capability analysis (which is not suitable in AMC's situation), the applicability and effectiveness of these methods depend on the choice of MOE. For instance, in terms of identifying the greatest opportunities for improvement, DR and TDT seem to be more informative than ADT. The results from Table 3.20 demonstrate the comparison of validity of the vital few identified by the different MOEs. The comparative Pareto chart is adapted to provide and is recommended as an alternative to the trend chart. It seems to the author that comparative Pareto chart is more informative than trend chart. The use of these SPC techniques are demonstrated in Chapter 2, 3, 4 and 5.

Based on the evaluation results, DR seems to be an all right MOE. However, the author is still not convinced that the attribute type of MOE can represent actual performance well. It is exciting that TDT seems to be an rational variable-type alternative. TDT actually considers the number of delays and delay time, which is a factor that DR ignores.

Average run length (ARL) analysis is applied to determine how often on-time performance information should be reported. The probability of detecting shifts and the sample size are two factors that vary with the reporting frequency, and there is clearly a trade-off to be made between them. The relationship between them is demonstrated in Chapter 4. Ultimately, AMC will have to balance this information with other considerations in order to determine a best reporting frequency

6.2 Future Work

As far as future work goes, the author has the following three recommendations.

First, the author used confidence interval to determine if there are significance differences in performance between different types of aircraft or the different number air forces. This could be generalized using Analysis of Variance (ANOVA) methods to make such multiple comparisons simultaneously, instead of pairwise. ANOVA could also be used to determine if there were significant interactions between such factors. It will be interesting to know that if the performance of each type of aircraft will perform differently among different subgroups.

Second, In Chapter 4, variable type of control charts exhibit wild behavior. As mentioned earlier, it might be the skewness of the overall delay time distribution that causes this. A possible alternative might be to develop charts on the mean and standard deviation of the delay time only for those aircraft that do not departure on-time.

Third, all the SPC techniques evaluated in this thesis are all on-line SPC techniques. The methods of off-line SPC, including design of experiments, might provide a better approach to alleviate assignable causes, in a more advanced way than the cause and effect diagram. It might be worthwhile to explore it.

Appendix A. The Tables of Vital Few Delay Codes Under Different MOE

C-17	**Delay Codes Identified by DR**
Rank	**Delay Code & Description**
1	106:Arrival station Weather prelude safe landing
2	279:Deviation required due to scheduling error
3	105:en route weather
4	923:Power Plant
5	104:Preclude takeoff
6	171:Load improperly configured
7	941:Air Conditioning
8	133:ATC delay
9	144:MOG
10	170:Customer provided equipment not ready
11	525:Deviation directed to support mission
12	141:Arrival station restricted
13	522:Deviation directed to Support MICAP
14	957:c-17 auto flight control
15	103:Precluded ground processing of aircraft
16	529:Other Management Deviation
17	222:Crew directed, no discripency found
18	140:Departure station restriction
19	521:Deviation directed by the US air force or DOE

Table A.1 The Top 19 Delay Codes for the C-17 (DR)

KC-10	**Delay Codes Identified by DR**
Rank	**Delay Code & Description**
1	507:Sympathetic Delay due to lead, receiver
2	104:Prelude take off
3	105:En route weather
4	106:Arrival station weather precluded a safe landing
5	923:Power Plant
6	946:Fuel system
7	133:ATC delay
8	942:Electronic power supply
9	199:Other miscellaneous deviation
10	222:Crew Directed, Maintenance requested
11	261:Deviation on sympathetic delay for leading
12	913:Landing gear
13	140:Departure station restricted
14	107:Late for deicing
15	141:Arrival Station Restricted
16	945:Hydraulic and pneumatic power supply
17	712:Stock level not maintain this type of aircraft
18	525:Deviation directed to support mission enhancement
19	172:Mission essential passenger later or no show

Table A.2 The Top 19 Delay Codes for the KC-10 (DR)

KC-135	Delay Codes Identified by DR
Rank	Delay Code & Description
1	507:Sympathetic Delay due to lead, receiver
2	132:Departure deviation to make good change
3	104:precluded takeoff
4	133:ATC delay
5	106:Arrival station weather prelude a safe landing
6	261:Deviation in sympathetic delay
7	279:Deviation due to scheduling error
8	105:En route weather
9	951:Instrument systems
10	946:Fuel system
11	199:other miscellaneous deviation
12	945:Hydraulic and pneumatic power supply
13	952:automatic flight controls
14	923:Power plant
15	299:other operations deviation
16	140:Departure station restrictions
17	914:flight control
18	107:Late for de icing, defogging
19	942:Electronic power supply

Table A.3 The Top 19 Delay Codes for the KC-135 (DR)

	Delay Codes Identified by DR	
Rank	Delay Code	Description
1	923	Power plant
2	105	En route weather
3	132	Departure deviation to make good change
4	104	Preclude take off
5	106	Arrival station weather precluded a safe landing
6	507	Sympathetic delay
7	914	Flight control
8	946	Fuel system
9	945	Hydraulic and pneumatic power supply
10	913	Landing gear
11	951	Instrument and independent system
12	140	Departure station restriction
13	941	Air conditioning
14	199	Other miscellaneous
15	942	Electronic Power plant
16	952	Automatic flight control
17	713	Stock level maintain, but the item is not listed
18	171	Load improperly configured
19	133	ATC delay

Table A.4 The Top 19 Delay Codes for the 15th NAF (DR)

	Delay Codes Identified by DR	
Rank	Delay Code	Description
1	507	Sympathetic delay
2	106	Arrival station weather precluded a safe landing
3	104	Precluded take off
4	521	Deviation directed to or validate to USAF, JCS, SD
5	140	Departure station restriction

Table A.5 the Top 19 Delay Codes for the UK NAF (DR)

	Delay Codes Identified by DR	
Rank	Delay Code	Description
1	507	Sympathetic delay
2	132	departure deviation to make good change
3	104	Precluded takeoff
4	106	Arrival station weather precluded a safe landing
5	105	En route weather
6	133	ATC delay
7	261	Deviation in Sympathetic delay
8	279	Deviation required due to scheduling error
9	946	Fuel system
10	951	Instrument
11	199	Other miscellaneous
12	923	Power plant
13	945	Hydraulic and pneumatic power supply
14	140	Departure station restriction
15	942	Electronic power supply
16	952	Automatic flight control
17	107	Late for de icing
18	172	Mission essential passenger late or no show
19	914	Flight control

Table A.6 The Top 19 Delay Codes for the Air Refueling Mission (DR)

	Delay Codes Identified by Average Delay Time	
Rank	Delay Code	Description
1	799	Other logistics deviation
2	976	ECM/C-17 Tactical Electronic warfare
3	712	Stock level not maintain this type of aircraft
4	207	Crew duty time insufficient
5	521	Deviation directed by in support of USAF, JCS, statement department
6	713	Stock level maintain this aircraft, but item not listed
7	119	Base operation
8	833	Saturation or shortage of supply equipment
9	911	Aircraft structure and window
10	523	Deviation directed or validated to support higher priority mission
11	143	Down line station restriction
12	513	Requested incorrected equipment or configuration to meet mission requirement
13	142	Down line station restriction
14	913	Landing gear
15	103	Precluded ground processing of aircraft
16	832	Station or shortage of personnel
17	999	Other logistics maintenance deviation
18	106	Arrival station weather precluded a safe landing
19	941	Air conditioning, pressurization and surface ice Control

Table A.7 The Top 19 Delay Codes for the C-17 (ADT)

	Delay Codes Identified by Average Delay Time	
Rank	Delay Code	Description
1	207	Crew duty time insufficient
2	522	Deviation directed to support MICAP
3	117	Lodging
4	947	Oxygen system
5	131	Held for inspection
6	945	Hydraulic and pneumatic power supply
7	913	Landing gear
8	949	Misc, utility
9	972	Radar navigation/INS
10	106	Arrival station weather precluded a safe landing
11	171	Load improperly
12	914	Flight control
13	141	Arrival station restriction
14	951	Instrument
15	103	Precluded ground process of aircraft
16	104	Precluded takeoff
17	113	Bomb threat
18	143	Down line station restriction
19	186	Emergency reconfiguration for air evacuation

Table A.8 The Top 19 Delay Codes for the KC-10 (ADT)

	Delay Codes Identified by Average Delay Time	
Rank	Delay Code	Description
1	713	Stock level maintain this aircraft, but item not listed
2	101	Outside air temperature dictated a change in fuel load
3	134	Non receipt of diplomatic clearance
4	712	Stock level not maintain this aircraft
5	521	Deviation directed in support USAF, JCS
6	506	Deviation to accommodate new slot time
7	523	Deviation directed or validated to support higher priority mission
8	151	Diplomatic clearance not received
9	200	Crew rest
10	915	Doors
11	715	Order and ship time not exceeds
12	122	Lodging
13	170	Customer provided equipment not ready
14	207	Crew duty time insufficient
15	529	Other management deviation
16	210	Crew availability
17	911	Airframe structure and window
18	507	Sympathetic delay
19	525	Deviation directed to support mission enhancement

Table A.9 The Top 19 Delay Codes for the KC-135 (ADT)

Mission	Delay Codes Identified by Average Delay Time	
Rank	Delay Code	Description
1	713	Stock level maintain, but the item is not listed
2	134	Non receipt of diplomatic clearance
3	799	Other logistic supply deviation
4	101	Outside temperature directed a change in fuel load
5	712	Stock Levels not maintain for this aircraft
6	718	Asset issued and formed to be unserviceable
7	505	Unit operation at or above command level
8	151	Diplomatic Clearance
9	521	Deviation directed by or in support USAF, JCS or SD
10	506	Deviation to accommodate new slot time
11	200	Crew rest
12	915	Doors
13	207	Crew duty time insufficient
14	715	Order and ship time not exceed
15	911	Airframe structure and windows
16	523	Deviation directed or support higher priority mission
17	122	Lodging
18	529	Other management deviation
19	941	air conditioning

Table A.10 The Top 19 Delay Codes for Air Refueling Mission (ADT)

C-17	Delay Codes Identified by Total Delay Time
Rank	Delay Code & Description
1	106:Arrival station weather precluded a safe landing
2	911:Unknown
3	799:Other logistics Supply Deviation
4	521:Deviation directed by or in support of USAF, JCS, state department
5	941:Air conditioning
6	833:Saturation or shortage of support equipment
7	525:Deviation directed to support aircrew enhancement
8	923:Power plant
9	279:Deviation required due to scheduling error
10	104:Precluded takeoff
11	207:Crew duty times insufficient
12	171:Load improperly configured, prepared, document or other wise not ready
13	913:Landing gear
14	523:Deviation directed or validated to support higher priority mission
15	144:MOG restrictions
16	103:Precluded ground processing of aircraft
17	999:Other logistics maintenance deviation
18	141:Arrival station restricted
19	529:Other management deviations

Table A.11 The Top 19 Delay Codes for the C-17 (TDT)

KC-10	Delay Codes Identified by Total Delay Time
Rank	**Delay Code & Description**
1	507:Sympathetic Delay due to lead, receiver
2	106:Arrival station weather precludes a safe landing
3	104:Precluded take off
4	134:Non receipt of diplomatic clearance
5	712:Stock level not maintain this type of aircraft
6	946:Fuels system
7	923:Power plant
8	941:Air conditioning
9	525:Deviation directed to support mission enhancement
10	207:Crew duty time insufficient
11	799:other logistics supply deviation
12	222:Crew directed; maintenance requested
13	140:Departure station restricted
14	951:Instrument/Independent system
15	913:Landing gear
16	141:Arrival station restriction
17	942:Electrical power supply
18	911:Airframe structure and windows
19	105:En route weather

Table A.12 The Top 19 Delay Codes for the KC-10 (TDT)

KC-135	Delay Codes Identified by Total Delay Time
Rank	**Delay Code & Description**
1	507:Sympathetic Delay due to lead, receiver
2	134:Non receipt of diplomatic clearance
3	104:Precluded takeoff
4	712:Stock level not maintain for this type of aircraft
5	106:Arrival station weather precluded a safe landing
6	132:Departure deviation to make a good chanced control time...
7	946:Fuel system
8	506:Deviation to accommodate new slot time
9	279:Deviation required due to scheduling error
10	923:Power plant
11	140:Departure station restriction
12	951:Instrument/Independent system
13	299:Other operational deviation
14	521:Deviation directed by or in support of USAF, JCS, state department
15	105:En route weather
16	913:Landing gear
17	529:Other management deviation
18	261:Sympathetic Delay
19	207:Crew duty time insufficient

Table A.13 The Top 19 Delay Codes for the KC-135 (TDT)

	Delay Codes Identified by Total Delay Time	
Rank	**Delay Code**	**Description**
1	923	Power plant
2	713	Stock level maintain, but the item is not listed
3	106	Arrival station weather precluded a safe landing
4	913	Landing gear
5	946	Fuel system
6	507	Sympathetic delay
7	914	Flight control
8	104	Precluded takeoff
9	945	Hydraulic and pneumatic power supply
10	941	air conditioning
11	207	Crew duty time insufficient
12	210	Crew availability
13	712	Stock Levels not maintain for this aircraft
14	911	Airframe structure and window
15	942	Electronic Power supply
16	523	Deviation directed to support higher priority mission
17	951	Instrument, independent system
18	222	Crew directed , maintenance requested
19	132	Departure deviation to make good change

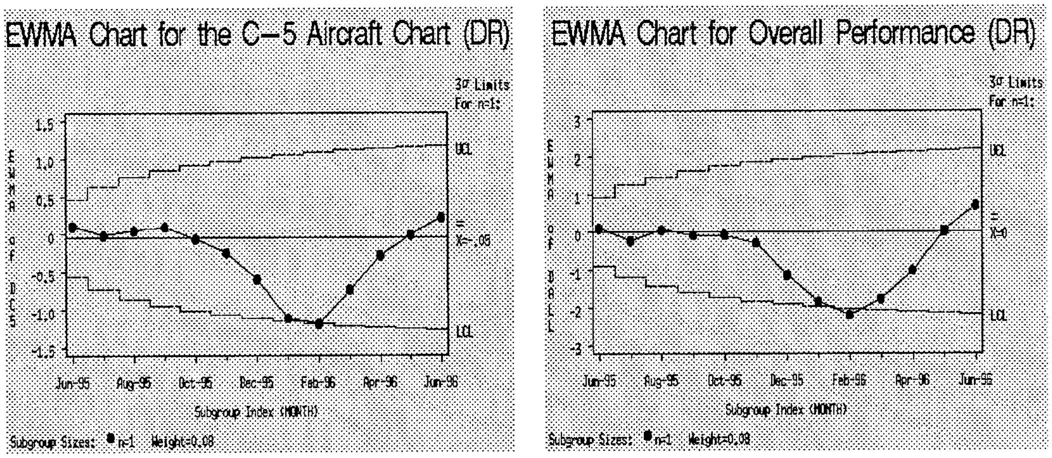
Table A.14 The Top 19 Delay Codes for the 15th NAF (TDT)

	Delay Codes Identified by Total Delay Time	
Rank	**Delay Code**	**Description**
1	507	Sympathetic delay
2	134	Non receipt of diplomatic clearance
3	521	Deviation directed to or validate to USAF, JCS, SD
4	999	Other logistics Maintenance
5	106	Arrival station weather precluded a safe landing

Table A.15 The Top 19 Delay Codes for the UK NAF (TDT)

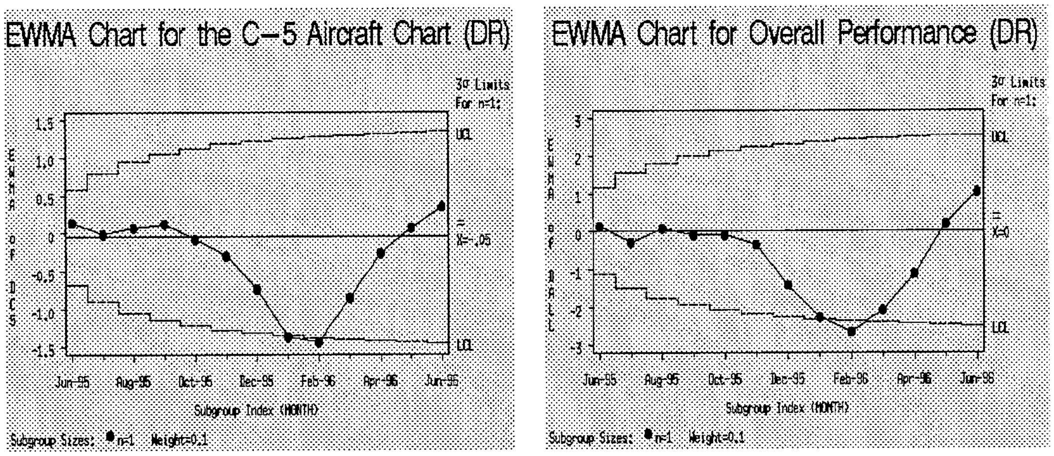
	Delay Codes Identified by Total Delay Time	
Rank	**Delay Code**	**Description**
1	507	Sympathetic Delay
2	134	No receipt of diplomatic clearance
3	104	Precluded takeoff
4	712	Stock Levels not maintain for this aircraft
5	106	Arrival station weather precluded a safe landing
6	946	Fuel system
7	923	Power plant
8	132	Depart deviation to make good change
9	279	Deviation required due to scheduling error
10	505	Unit operating at or above commitment level
11	140	Departure station restriction
12	951	Instrument independent system
13	525	Deviation directed to supply mission enhancement
14	207	Crew duty time insufficient
15	941	Air conditioning
16	913	Landing gear
17	105	En route weather
18	942	Electronic power plant
19	521	Deviation directed by or in support USAF, JCS or SD

Table A.16 The Top 19 Delay Codes for Air Refueling Mission (TDT)



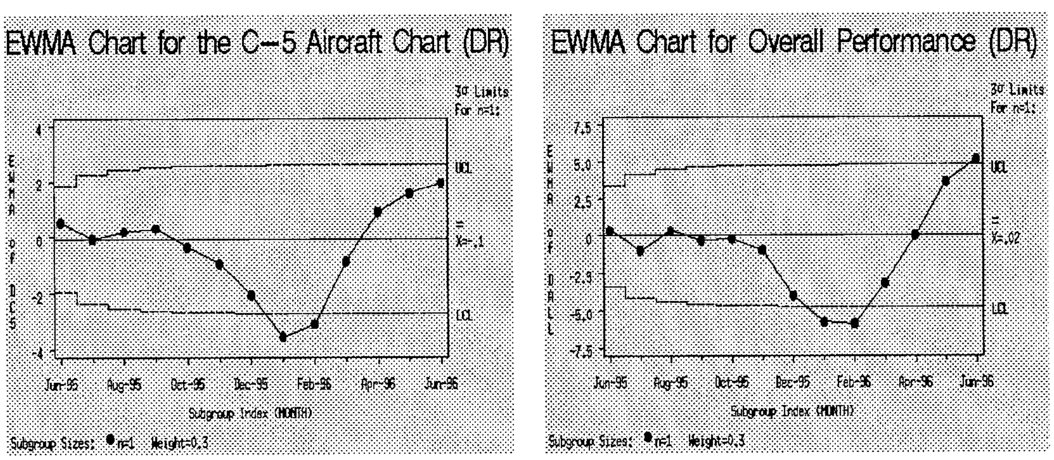
(a) (b)

Figure B.1 EWMA Charts of Overall DR and C-5 DR Performance with Different λ Values (a)C-5: $\lambda = 0.08$ (b) Overall $\lambda = 0.08$



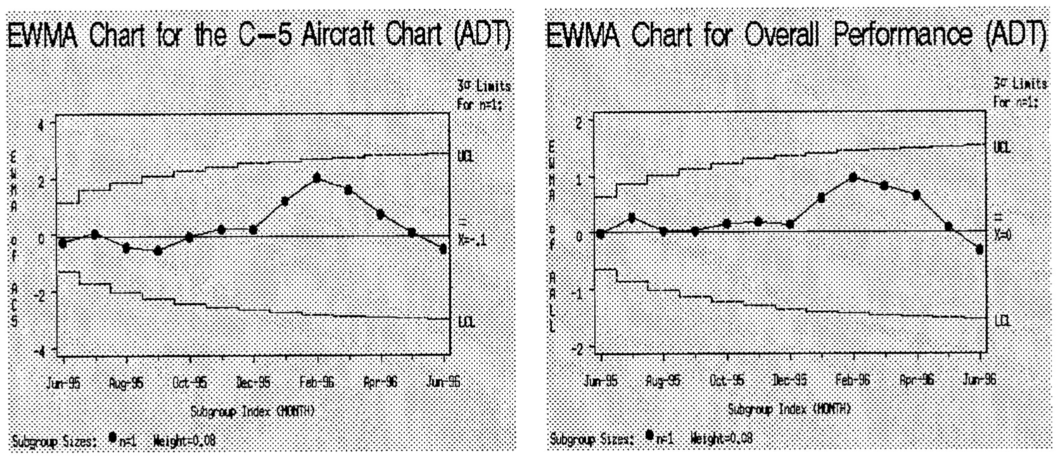
(a) (b)

Figure B.2 EWMA Charts of Overall DR and C-5 DR Performance with Different λ Values (a) C-5: $\lambda = 0.1$ (b) Overall $\lambda = 0.1$



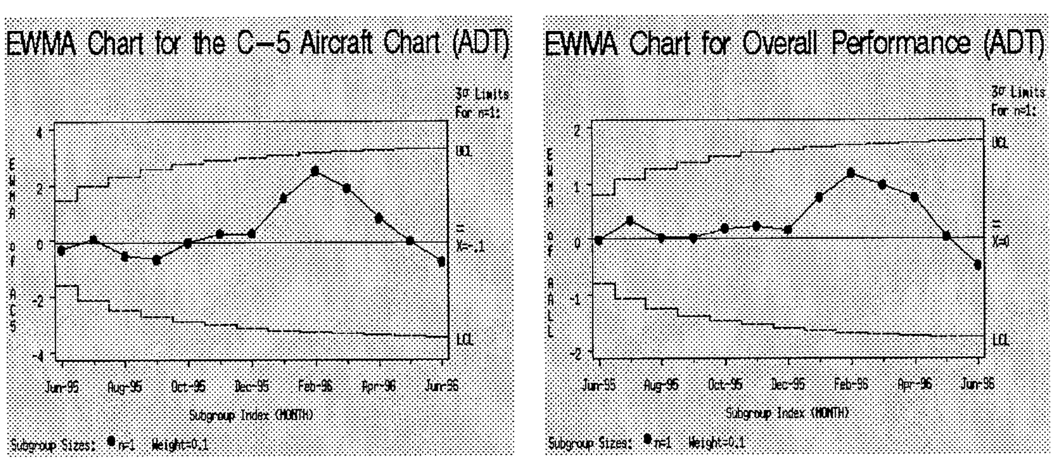
(a) (b)

Figure B.3 EWMA Charts of Overall DR and C-5 DR Performance with Different λ Values (a) C-5: $\lambda = 0.3$ (b) Overall $\lambda = 0.3$



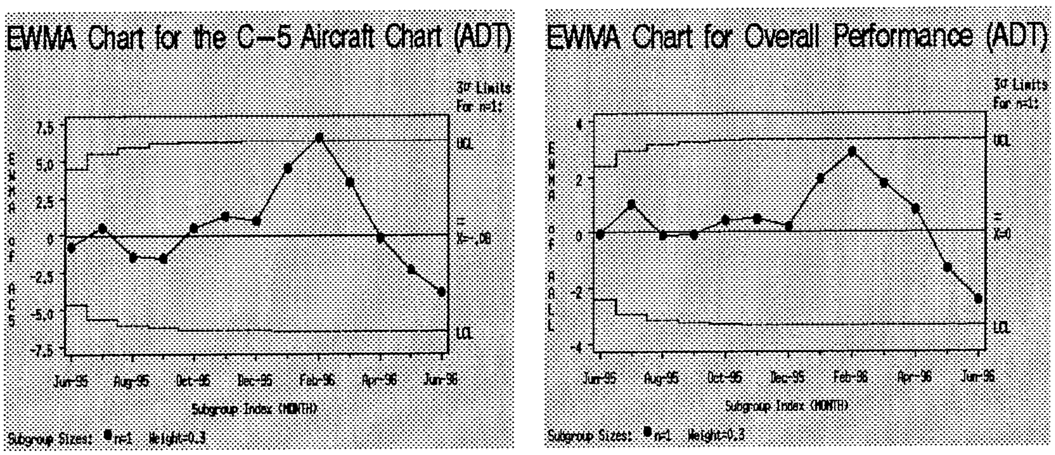
(a) (b)

Figure B.4 EWMA Charts of Overall ADT and C-5 ADT Performance with Different λ Values (a)C-5: $\lambda = 0.08$ (b) Overall $\lambda = 0.08$



(a) (b)

Figure B.5 EWMA Charts of Overall ADT and C-5 ADT Performance with Different λ Values (a) C-5: $\lambda = 0.1$ (b) Overall $\lambda = 0.1$



(a) (b)

Figure B.6 EWMA Charts of Overall ADT and C-5 ADT Performance with Different λ Values (a) C-5: $\lambda = 0.3$ (b) Overall $\lambda = 0.3$

Appendix C. Equation Derivation

This appendix proves the equation in Chapter 5.

$$DR_{overall} = \sum_{i=1}^{5} P_i * DR_i$$

Assume

$$\begin{aligned}
DR_i &= \text{DR for aircraft type} \\
n_i &= \text{Number of misssion, for type i aircraft} \\
d_i &= \text{Number of delays, for type i aircraft} \\
n &= \text{Total number of missions} = \sum_{i=1}^{5} n_i \\
n &= \text{Total number of missions} = \sum_{i=1}^{5} n_i = \sum_{i=1}^{5} d_i \\
P_i &= \text{Proportion of mission} = \frac{n_i}{n}
\end{aligned}$$

then

$$\begin{aligned}
\sum_{i=1}^{5} P_i * DR_i \qquad &= \textstyle\sum_{i=1}^{5}(\frac{n_i}{n})(1 - \frac{d_i}{n_i}) \\
&= \textstyle\sum_{i=1}^{5}(\frac{n_i}{n} - \frac{d_i}{n_i}) \\
&= 1/n * \textstyle\sum_{i=1}^{5}(n_i - d_i) \\
&= 1/n(\textstyle\sum_{i=1}^{5} n_i - \sum_{i=1}^{5} d_i) \\
&= \tfrac{n}{n} - \tfrac{d}{n} \\
&= 1 - \tfrac{d}{n} \\
&= DR_{overall}
\end{aligned}$$

Appendix D. Average Run Length Table for EWMA

	Parameter		α Weight parameter)					
1	h	δ	0.05	0.10	0.25	0.50	0.75	1.00
2	2.0	0	127.53	73.28	38.56	26.45	22.88	21.98
3	2.0	0.25	43.94	34.49	24.83	20.12	18.86	19.13
4	2.0	0.5	18.97	15.53	12.74	11.89	12.34	13.70
5	2.0	0.75	11.64	9.36	7.62	7.29	7.86	9.21
6	2.0	1	8.38	6.62	5.24	4.91	5.26	6.25
7	2.0	1.25	6.56	5.13	3.96	3.59	3.76	4.4
8	2.0	1.5	5.41	4.2	3.19	2.8	2.84	3.24
9	2.0	1.75	4.62	3.57	2.68	2.29	2.26	2.49
10	2.0	2.00	4.04	3.12	2.32	1.95	1.88	2.00
11	2.0	2.25	3.61	2.78	2.06	1.7	1.61	1.67
12	2.0	2.5	3.26	2.52	1.85	1.51	1.42	1.45
13	2.0	2.75	2.99	2.32	1.69	1.37	1.29	1.29
14	2.0	3.00	2.76	2.16	1.55	1.26	1.19	1.19
15	2.0	3.25	2.56	2.03	1.43	1.18	1.13	1.12
16	2.0	3.75	2.26	1.83	1.24	1.08	1.05	1.04
17	2.0	4.00	2.15	1.73	1.17	1.05	1.03	1.02

Table D.1 Average Run Length Table for Two-Sided EWMA Chart

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